Analyzing global typologies of socio-ecological vulnerability

The cases of human security in drylands, and rapid coastal urbanization

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Abstract

On a planetary scale human populations need to adapt to both socio-economic and environmental problems amidst rapid global change. This holds true for coupled human-environment (socio-ecological) systems in rural and urban settings alike. Two examples are drylands and urban coasts. Such socio-ecological systems have a global distribution. Therefore, advancing the knowledge base for identifying socio-ecological adaptation needs with local vulnerability assessments alone is infeasible: The systems cover vast areas, while funding, time, and human resources for local assessments are limited. They are lacking in low an middle-income countries (LICs and MICs) in particular.

But places in a specific socio-ecological system are not only unique and complex – they also exhibit similarities. A global patchwork of local rural drylands vulnerability assessments of human populations to socio-ecological and environmental problems has already been reduced to a limited number of problem structures, which typically cause vulnerability. However, the question arises whether this is also possible in urban socio-ecological systems. The question also arises whether these typologies provide added value in research beyond global change. Finally, the methodology employed for drylands needs refining and standardizing to increase its uptake in the scientific community. In this dissertation, I set out to fill these three gaps in research.

The geographical focus in my dissertation is on LICs and MICs, which generally have lower capacities to adapt, and greater adaptation needs, regarding rapid global change. Using a spatially explicit indicator-based methodology, I combine geospatial and clustering methods to identify typical configurations of key factors in case studies causing vulnerability to human populations in two specific socio-ecological systems. Then I use statistical and analytical methods to interpret and appraise both the typical configurations and the global typologies they constitute.

First, I improve the indicator-based methodology and then reanalyze typical global problem structures of socio-ecological drylands vulnerability with seven indicator datasets. The reanalysis confirms the key tenets and produces a more realistic and nuanced typology of eight spatially explicit problem structures, or vulnerability profiles: Two new profiles with typically high natural resource endowment emerge, in which overpopulation has led to medium or high soil erosion. Second, I determine whether the new drylands typology and its socio-ecological vulnerability concept advance a thematically linked scientific debate in human security studies: what drives violent conflict in drylands? The typology is a much better predictor for conflict distribution and incidence in drylands than regression models typically used in peace research. Third, I analyze global problem structures typically causing vulnerability in an urban socio-ecological system - the rapidly urbanizing coastal fringe (RUCF) – with eleven indicator datasets. The RUCF also shows a robust typology, and its seven profiles show huge asymmetries in vulnerability and adaptive capacity. The fastest population increase, lowest income, most ineffective governments, most prevalent poverty, and lowest adaptive capacity are all typically stacked in two profiles in LICs. This shows that beyond local case studies tropical cyclones and/or coastal flooding are neither stalling rapid population growth, nor urban expansion, in the RUCF. I propose entry points for scaling up successful vulnerability reduction strategies in coastal cities within the same vulnerability profile.

This dissertation shows that patchworks of local vulnerability assessments can be generalized to structure global socio-ecological vulnerabilities in both rural and urban socio-ecological systems according to typical problems. In terms of climate-related extreme events in the RUCF, conflicting

problem structures and means to deal with them are threatening to widen the development gap between LICs and high-income countries unless successful vulnerability reduction measures are comprehensively scaled up. The explanatory power for human security in drylands warrants further applications of the methodology beyond global environmental change research in the future. Thus, analyzing spatially explicit global typologies of socio-ecological vulnerability is a useful complement to local assessments: The typologies provide entry points for where to consider which generic measures to reduce typical problem structures – including the countless places without local assessments. This can save limited time and financial resources for adaptation under rapid global change.

Zusammenfassung

Menschliche Gesellschaften müssen sich weltweit an sozioökonomische und ökologische Probleme unter rapidem globalen Wandel anpassen. Dies gilt für gekoppelte Mensch-Umwelt-Systeme (sozio-ökologische Systeme) in ländlichen und in städtischen Gebieten. Beispiele sind Trockengebiete oder urban geprägte Küsten. Solche sozio-ökologischen Systeme haben eine globale Ausdehnung. Daher ist es nicht praktikabel, die Wissensbasis zur Ermittlung des sozio-ökologischen Anpassungsbedarfs allein mit lokalen Vulnerabilitätsanalysen voranzutreiben: Die Systeme decken große Gebiete ab, während finanzielle Mittel, Zeit und Personal für lokale Analysen begrenzt sind. In Ländern mit niedrigem und mittlerem Einkommen (LICs und MICs) mangelt es daran besonders.

Aber Orte in einem konkreten sozioökologischen System sind nicht nur einzigartig und komplex - sie weisen auch Gemeinsamkeiten auf. Ein globaler Flickenteppich lokaler Vulnerabilitätsanalysen von Gesellschaften gegenüber sozioökonomischen und ökologischen Problemen in Trockengebieten wurde bereits auf eine begrenzte Anzahl von Problemstrukturen reduziert, die typischerweise Verwundbarkeiten verursachen. Es stellt sich jedoch die Frage, ob dies auch in urbanen sozioökologischen Systemen möglich ist. Es stellt sich auch die Frage, ob diese Typologien über die Forschung zum globalen Wandel hinaus einen Mehrwert bieten. Schließlich muss die für Trockengebiete angewandte Methodik verfeinert und standardisiert werden, um ihre Aufnahme in der Wissenschaft zu erhöhen. In dieser Dissertation habe ich versucht, diese drei Forschungslücken zu schließen.

Der geografische Schwerpunkt meiner Dissertation liegt auf LICs und MICs, die im Allgemeinen über geringere Anpassungskapazitäten und einen größeren Anpassungsbedarf gegenüber schnellen globalen Wandels verfügen. Unter Verwendung einer räumlich expliziten, indikatorgestützten Methodik kombiniere ich raumbezogene und Clustering-Methoden, um typische Konfigurationen von Schlüsselfaktoren in Fallstudien zu identifizieren, die Verwundbarkeiten für Gesellschaften in zwei spezifischen sozio-ökologischen Systemen verursachen. Dann benutze ich statistische und analytische Methoden, um sowohl die typischen Konfigurationen als auch die globalen Typologien zu interpretieren und zu bewerten.

Im ersten Teil verbessere ich die indikatorbasierte Methodik und reanalysiere dann typische globale Problemstrukturen sozioökologischer Verwundbarkeit in ländlichen Trockengebieten mit sieben Indikatordatensätzen. Die Reanalyse bestätigt die Kernaussagen und führt zu einer realistischeren und differenzierteren Typologie von acht räumlich expliziten Problemstrukturen bzw. Vulnerabilitätsprofilen: Zwei neue Profile mit typischer hoher natürlicher Ressourcenausstattung treten auf, in denen Überbevölkerung zu mittlerer bis hoher Bodenerosion geführt hat. Im zweiten Teil stelle ich fest, ob die neue Trockengebietstypologie und ihr sozioökologisches Vulnerabilitätskonzept eine thematisch verknüpfte wissenschaftliche Debatte über menschliche Sicherheit vorantreiben können: Was treibt gewalttätige Konflikte in Trockengebieten an? Die Typologie ist ein deutlich besserer Prädiktor für die Verteilung und Inzidenz von Konflikten in Trockengebieten als Regressionsmodelle, die typischerweise in der Friedensforschung verwendet werden. Im dritten Teil analysiere ich mit elf Indikatordatensätzen globale Problemstrukturen, die in einem urbanen sozioökologischen System - der rapide urbanisierenden Küstenzone (RUCF) – typischerweise Verwundbarkeiten verursachen. Die RUCF weist ebenfalls eine robuste Typologie auf und ihre sieben Profile zeigen große Asymmetrien in Bezug auf Vulnerabilität und Anpassungskapazität. Der schnellste Bevölkerungszuwachs, das

niedrigste Einkommen, die ineffektivsten Regierungen, die am weitesten verbreitete Armut und die geringste Anpassungskapazität sind typischerweise in zwei Profilen in LICs geballt. Dies zeigt jenseits von lokalen Analysen, dass tropische Wirbelstürme und / oder Überschwemmungen im RUCF weder schnelles Bevölkerungswachstum noch städtische Expansion verhindern. Ich schlage Einstiegspunkte für die Skalierung erfolgreicher Strategien zur Reduzierung von Vulnerabilität in Küstenstädten innerhalb des gleichen Vulnerabilitätsprofils vor.

Diese Dissertation zeigt, dass Flickenteppiche lokaler Vulnerabilitätsanalysen verallgemeinert werden können, um globale sozioökologische Vulnerabilitäten in ländlichen und städtischen sozioökologischen Systemen nach typischen Problemstrukturen zu systematisieren. In Bezug auf klimatische Extremereignisse drohen sich entgegenstehende Problemstrukturen und Mittel, um mit ihnen umzugehen, die Entwicklungslücke zwischen LICs und Ländern mit hohem Einkommen in der RUCF zu vergrößern, wenn erfolgreiche Maßnahmen zur Vulnerabilitätsreduzierung nicht umfassend ausgeweitet werden. Die Erklärungskraft für menschliche Sicherheit in Trockengebieten berechtigt weitere Anwendungen der Methodik über die globale Umweltforschung hinaus. Die Analyse räumlich expliziter globaler Typologien sozio-ökologischer Vulnerabilität ist daher eine sinnvolle Ergänzung zu lokalen Analysen: Die Typologien bieten Einstiegspunkte dafür, welche generischen Maßnahmen wo in Betracht zu ziehen, um typische Problemstrukturen zu reduzieren - einschließlich der unzähligen Orte ohne lokale Analysen. Dies kann begrenzte Zeit und finanzielle Ressourcen für Anpassung unter rapidem globalen Wandel sparen.

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The truth is, Pavlov's dog trained Pavlov to ring his bell just before the dog salivated – G. Carlin.

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Contributing Scientific Publications

This cumulative dissertation contains the three following publications numbered 1 to 3. Publications 1 and 2 are published in ISI-listed journals. Publication 3 has been submitted to an ISI-listed journal and is currently in review. I am the lead author of two publications (2 and 3), and co-author of one (1).

1) Kok, M., Lüdeke, M., Lucas, P., Sterzel, T., Walther, C., Janssen, P., Sietz, D & de Soysa, I. (2015). A new method for analysing socio-ecological patterns of vulnerability. *Regional Environmental Change*, 16(1), 229-243.

2) Sterzel, T., Lüdeke, M., Kok, M., Walther, C., Sietz, D., de Soysa, I., Lucas, P. & Janssen, P. (2014). Armed conflict distribution in global drylands through the lens of a typology of socio-ecological vulnerability. *Regional Environmental Change*, 14(4), 1419-1435.

3) Sterzel, T., Lüdeke, M., Walther, C., Kok, M., Sietz, D., & Lucas, P. (2015). Global typology of urban coastal vulnerability under rapid urbanization. Submitted to *PLoS One*, *in review.*

The following book chapter and two reports are additional publications that directly or indirectly resulted from my research for this dissertation:

Sterzel, T., Orlowsky, B., Förster, H., Weber, A., & Eucker, D. (2015). Climate Change Vulnerability Indicators: From Noise To Signal. In *The World of Indicators: The Making of Governmental Knowledge through Quantification* (pp. 307–328), edited by R. Rottenburg, S. Merry, S.-J. Park, & J. Mugler. Cambridge: Cambridge University Press.

Lüdeke, M. K. B., Walther, C., Sterzel, T., Kok, M. T. J., Lucas, P., Janssen, P., & Hilderink, H. (2014). *Understanding Change in Patterns of Vulnerability*. Potsdam. Potsdam Institute for Climate Impact Research (PIK). urn:nbn:de:kobv:b103-pik1274.

Kok, M., Lüdeke, M., Sterzel, T., Lucas, P., Walter, C., Janssen, P., & Soysa, I. (2010). *Quantitative analysis of patterns of vulnerability to global environmental change*. Den Haag. Netherlands Environmental Assessment Agency (PBL). http://www.pbl.nl/bibliotheek/rapporten/550025005.pdf.

List of Abbreviations

AIC	Akaike Information Criterion
AR4	Fourth Assessment Report
GEC	Global environmental change
GEO 4	Fourth Global Environmental Outlook
IMR	Infant Mortality Rate
IPCC	Intergovernmental Panel on Climate Change
LDCs	Least Developed Countries
LICs	Low-income countries
LMICs	Low- and middle-income countries
MICs	Middle-income countries
ROC	Receiver Operating Characteristic
RUCF	Rapidly urbanizing coastal fringe
TAR	Third Assessment Report
UCDP/PRIO ACD	Armed Conflict Dataset, Uppsala Conflict Data Program and International Peace Research Institute, Oslo
UNDESA	United Nations Department of Economic and Social Affairs
UNEP	United Nations Environmental Programme

„The way we try to reduce the complexity in the world is by looking for patterns... We take all the particles we know today and we have to fit them to into some kind of underlying structure - are they the remnants of some more … complete picture...?“

Prof. David Kaplan in the documentary „Particle Fever“

“The macroscope is the ability to look at the overview, to drop the detail, ... to look for patterns in the relationship between things.”

Ken Webster - “Systems Thinking and the Circular Economy - An Introduction”

1 Introduction and Overview

1.1 General Introduction

In recent decades, global change has continually placed higher demands on humans and the environment to adapt. Unmanaged urbanization, urban expansion, and resource demand increase are radically changing the environment (Bloom et al. 2008; Grimm et al. 2008; Seto et al. 2011). The increase of greenhouse gas emissions over the past decades has increasingly emphasized the importance of climate change adaptation (Burkett et al. 2014). What these exemplary human-environment interactions have in common are rapid changes on a global scale (Steffen et al. 2011) for coupled human-environment systems.

On this scale, these changes in human-enviroment interactions require identifying socio-ecological adaptation needs, and successfully adapting accordingly. The rapidity of global change is often greater in low- and middle-income countries (LMICs), which generally have a lower capacity to adapt than high-income countries (HICs). Their institutional structures are often weaker, or missing (Jones et al. 2010). Therefore, adaptation is particularly urgent in LMICs.

This is fundamentally challenging, because funding and human resources for adaptation remain explicitly limited (Stecker et al. 2012). The financial gap between the funding recently announced and signed to climate change adaptation versus the estimated funding required illustrates this limitation: The gap currently amounts to approximately USD 90bn annually. This is the difference between what the world's biggest fund for climate change adaptation currently has at its disposal, and the USD 100bn of financial support the Paris Agreement urges high-income countries to annually support LMICs with starting 2020 (Green Climate Fund 2017; United Nations 2015). However, this amount is not solely designated for climate change adaptation, but also for mitigation (United Nations 2015). Before the inception of the Green Climate Fund, Costa et al. (2014) found that a mere USD 3.6bn of adaptation funds were attributed to receiving countries based on climate finance reporting to the UNFCCC.

Even if all the required funds were available for adaptation, a further challenge would remain: Adapting to climate change requires an understanding of underlying vulnerabilities in coupled human-environment systems, i.e. socio-ecological systems (Bierbaum et al. 2007; J. Gupta et al. 2010). Vulnerability is a concept used to establish needs, and current baselines, for adaptation to global change on global, regional, and local scales. Consequently, socio-ecological vulnerability has become an instrumental concept in global environmental change (GEC) research.

Socio-ecological vulnerability is the outcome of multiple stressors, actors, and contexts on various spatial and time scales (Patt et al. 2008; Turner et al. 2003). With this complexity in mind, it is understandable that vulnerability is commonly assessed on a case by case basis on a local or a regional scale - for example for a city or a for specific delta region. Often, these case studies are ambiguous in defining vulnerability and combining components to operationalize the definition (Costa et al. 2012; Hinkel 2011). Pairing these ambiguities with multiple stressors, actors, contexts, and scales that potentially shape vulnerability has led to a flurry of different methods used for vulnerability assessments on all spatial scales (Füssel 2009; Hinkel 2011; Sterzel et al. 2015).

It becomes clear that the case-by-case modus operandi for assessing vulnerability to identify adaptation needs across developing countries, let alone globally, is venturesome: First, it is unfeasible to conduct local assessments at all potentially affected locations (Schröter et al. 2005) due to limited financial and human resources. Therefore, local assessments will never render a complete picture of adaptation needs, nor will they unconditionally apply to the countless locations or regions left unassessed. Second, many methodologies are focused on the complexity and uniqueness (of vulnerability) of a specific place or system on a local level – regardless of similarities with other places. Therefore, deriving urgently needed implications of local assessments for vulnerability reduction on a regional or global level remain infeasible, and incommunicable, without systematically aggregating or generalizing patchworks of case study results. Yet there is a lack of data-driven methodologies for doing this.

To fit the adaptation bill on a global level, current vulnerability reduction is strongly reliant on scaling up case study knowledge. It is considered particularly important to produce generalizable insights into the processes that generate or reduce vulnerability (Schröter, Polsky, et al. 2005). Therefore it greatly adds value to a) know whether outcomes of (vulnerability) assessments are relevant for comparable places elsewhere in the world (German Advisory Council on Global Change (WBGU) 2016; Kasperson et al. 2005), and b) know where these places are. This incentivizes studies that identify general features and problem structures among the diversity of local case studies across the globe in the same kind of system: causal and spatial patterns of vulnerability to multiple socio-economic and environmental (i.e. biophysical) stressors.

The complex interplay of local and nonlocal influences under global change makes each place unique in the detail. However, places also share common properties and similarities with other places. Complexity can thus be reduced by an empirical search for patterns, or similarities, across places in a given socio-ecological system. Manila, Shanghai, Kolkata, and Santo Domingo are unique cities, and at the same time they are coastal, low-lying, fast growing, and exposed to tropical cyclones. Based on the richness of knowledge from case studies in a socio-ecological system, we can therefore determine whether they share underlying problem structures. Doing so could efficiently aid in establishing a more complete picture of adaptation needs.

Against this background, this dissertation aims to increase the understanding of global causal and spatial patterns of vulnerability. The dissertation thereby focuses on vulnerability of human populations to multiple socio-economic and environmental stressors in two specific socio-ecological systems with global distribution. One system - drylands - is largely rural, and one system – the rapidly urbanizing coastal fringe (RUCF) - is urban. In drylands, we additonally investigate a major societal outcome with conceivable links to socio-ecological vulnerability in drylands, i.e. violent conflict.

By increasing our understanding in these socio-ecological systems this analysis ultimately aids vulnerability reduction to socio-ecological problems in specific contexts in a world with limited financial and human resources for vulnerability assessment and adaptation. While the extent of analysis is global, it focuses on regional and local specifics on a subnational level of detail.

1.2 Methodological Introduction: Indicator-based Vulnerability Analysis for Global Assessment

1.2.1 Indicator-based Vulnerability Analysis

The concept of vulnerability is central to this dissertation. Vulnerability has been applied in a variety of fields of research including natural hazards (Cutter et al. 2006, 2008), climate change (Barros et al. 2014; Harrison et al. 2015; Ionescu et al. 2008), and GEC (McCubbin et al. 2015; Schröter, Cramer, et al. 2005; Szabo et al. 2016). The climate change and GEC communities most frequently apply the definition of vulnerability from the Third (TAR) and Fourth Assessment

Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC). My dissertation uses this definition of vulnerability as well: Vulnerability is defined as

> „The degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity." (Parry et al. 2007; White et al. 2001).

Importantly, the definition from AR4 accommodates for the assessment of coupled socio-ecological systems, and continues to dominate practice due to challenges in operationalizing the more recent definition from the Fifth Assessment Report (Fritzsche et al. 2014).

To date, no general framework exists for operationalizing the definition from the TAR and AR4 for the assessment of socio-ecological vulnerability. Instead, a wealth of index-based methodologies is commonly applied on various spatial and temporal scales in order to reduce the complex interplay of local and non-local influences on vulnerability. These methodologies employ datasets as indicators to quantify and measure components, which have been identified as relevant for vulnerability. The indicators are numerically aggregated to a single composite indicator, or index, using all kinds of methodologies. Then, these indices are employed for comparing the vulnerability of entities (e.g. populations, sectors, or groups of people) and for ranking them accordingly. In some cases, the resulting rankings allow to broadly inform decision-making as to where to prioritize vulnerability reducing measures, or their funding (Brooks 2009). Applications of index-based approaches are abundant on all spatial scales – at the level of countries (Diffenbaugh et al. 2007; Perch-Nielsen 2010), of districts or counties (Antwi-Agyei et al. 2012; Hahn et al. 2009), or cities and communities (Hallegatte et al. 2013; Hanson et al. 2011).

However, there are well-documented shortcomings of index-based rankings in quantitative, indicator-based studies. First, the aggregation of the indicators to an index comes at substantial costs: It obscures the structures that cause and contextualize vulnerability (Adger et al. 2004; Preston et al. 2011). These structures, however, are pivotal for systematically identifying specific adaptation needs. As a result, index-based analyses show which entities have a *similar value of overall vulnerability, and not similar causes*. On this basis, they suggest which entities to prioritize for vulnerability reduction. But they do not suggest how to reduce vulnerability, because the causes are obscured. As a result, many applications of indices for identifying adaptation needs beyond the local scale of analysis (i.e. for regions, or countries, in global overviews) are commonly contested on grounds of how they had simplistically reduced complexity (Barnett et al. 2008; Hinkel 2011; Füssel 2009; Sterzel et al. 2015).

The second point of contention is how relationships and dependencies between variables (i.e. indicator datasets) are defined in order to determine vulnerability. In most cases a linear combination of the indicators is chosen. This implies that each indicator's influence on the aggregated vulnerability index is independent from the values of the remaining indicators. This additive approach cannot reproduce relationships in which one indicator is the condition for the effect of another. For instance, the effect of an indicator A (such as frequency of storm surges - an environmental factor) on an overall household vulnerability index to flooding can depend on an indicator B (such as average household income - a socio-economic factor). In some studies more advanced formulations have been applied to reflect the mentioned interdependencies between input indicators (quadratic forms, fuzzy logic (Lüdeke et al. 2004), or decision trees (Cassel-Gintz et al. 1997)). These approaches depend on additional inductive choices of specific mathematical form and parameters, which are hardly verifiable. In this sense they define, rather than measure, vulnerability.

These shortcomings emphasize a real need for indicator-based methodological alternatives, especially when it comes to

- systematically structuring and classifying causes of vulnerability in assessed and unassessed places,
- and integrating local and regional specifics into spatially explicit global overviews.

As an alternative, we advocate analyzing the data space of the indicators chosen to quantify the causes of vulnerability, consisting of different values for different places. Instead of obscuring, or even omitting, the potential wealth of information in the multidimensional data space through a coarse index, we propose to exploit it, e.g. with data-driven methods for recognizing structures. If structures, or patterns, in the data space are evident and robust, then they can be interpreted in terms of severity and vulnerability reduction. These methods would also allow the data structure to "do the talking", instead of imposing assumed relationships between indicators on to the data.

1.2.2 Vulnerability Pattern Analysis: Methodological Achievements so far

The premise of vulnerability pattern analysis is that different places exhibit similar local and nonlocal socio-ecological interactions, which cause vulnerability. If vulnerability is similarly caused in a multitude of individual case studies, then complexity can be systematically reduced to more general, typical cases.

Vulnerability patterns analysis was inspired by the syndrome approach**,** which decomposes global change into typical patterns, or syndromes (Schellnhuber et al. 1997). This approach took a global view on regional and local dynamics of unsustainable interactions in systems under global change (Lüdeke et al. 2004; Petschel-Held et al. 1999; Schellnhuber et al. 1997). It structured these dynamics according to typical causal interactions as opposed to isolated influences (Manuel-Navarrete et al. 2007). The inductive approach hypothesized these interactions in a qualitative way. Then, the indicator datasets for quantifying these interactions were aggregated to an index. This masked underlying structures in the data, and lacked a basis for the systematic classification of interactions.

The Fourth Global Environmental Outlook (GEO 4) of the United Nations Environmental Programme (UNEP) transferred the syndrome approach to analyzing vulnerability of human populations to multiple stressors in socio-ecological systems. GEO 4 used the concept of vulnerability to frame problems the environment poses for human development in different socio-ecological systems (Jäger et al. 2007; Kok et al. 2009). The global assessment aimed to enhance its relevance for (subnational) regions and countries by looking for similarities between regions and countries, without ranking them with coarse indices. Through reviews of ample local and regional case studies in different parts of the world it became evident that vulnerability had a limited number of typical causes within each assessed socio-ecological system. These systems included smallholder farmers in global drylands, human populations in the rapidly urbanizing coastal fringe, and the global commons. An example of a typical causal combination for vulnerability of smallholder farmers in different places in the socio-ecological system of drylands was low market access through poor infrastructure and, thus, impeded acquisition of inputs to enhance low agricultural productivity and few opportunities for selling products. However, the reviews of the above-mentioned systems were purely qualitative.

Therefore, a data-driven indicator-based approach for global and regional scales was developed. Causes were quantified with indicators. The focus was on typical indicator value combinations, and keeping the indicators disaggregated. This balanced reducing complexity with preserving typical problem structures causing vulnerability in multitudes of different cases and places (Sietz et al. 2011, 2006; Lüdeke et al. 2014; Kok et al. 2010; Neumann et al. 2015). Cluster analysis methods were employed to determine whether typical structures exist in the data, i.e., typical problem structures causing vulnerability.

In order to develop empirically-based theories, one needs typical features, or regularities, to build upon (Janssen et al. 2012). Cluster analysis is a method of choice to identify such regularities in GEC research and socio-ecological systems alike. The choice of the specific clustering method depends on the aim of the investigation: If the focus is on similarity in the quantitative values of indicators, a method which identifies spherical and compact clusters is more appropriate than a method which, e.g., emphasizes connectedness as a cluster property. For the former, dimension reduction and topology, or in interpreting the numerical values of the cluster centers, may be the primary focus. In the first case one may consider a method based on self-organized maps (Kohonen 1982). This results in a map of minimal dimensionality, which preserves the neighborhood relations of the clusters. In the second case a partitioning method like k-means (Milligan et al. 1987) is the most direct approach. Since quantitative research in GEC and socio-ecological systems can be data-intensive computationally, methods which are suitable for larger datasets are particularly attractive.

1.2.3 Research Gaps

In the past, the literature has focused on local-level vulnerability assessments to capture complexity in a clearly defined, manageable field of interest. For the analysis of socio-ecological systems, however, it is crucial to both identify and analyze relationships at different spatial scales (Ostrom 2009). Therefore, fully understanding, or analyzing, local vulnerability also requires integrating context and cause-effect relationships from the regional and global scale. There is a lack of methodologies in socio-ecological vulnerability analysis that take this into account.

However, since GEO 4, a growing body of literature has been applying and advancing pattern recognition methods for analyzing causes of vulnerability in different socio-ecological systems on global and regional scales, while also integrating local specifics. In a study, which is important for this dissertation, Kok et al. (2010) started exploring global patterns of vulnerability, and their subnational spatial distributions, for drylands, forest overexploitation, and coastal urbanization on a more quantitative basis than GEO 4. Sietz et al. (2011) extended the analysis in drylands by verifying the patterns with 20 local case studies. Based on formal knowledge gained in these studies Janssen et al. (2012) synthesized the state of experience in using cluster analysis to understand coupled socio-ecological systems. Using similar methodologies, Neumann et al. (2015) found that typical ecological patterns underpin human out-migration in drylands, and Oberlack et al. (2016) found that typical socio-ecological patterns underpin how large-scale land acquisitions affect rural livelihoods. Oberlack and Eisenack identified typical patterns of barriers for adapting water governance to climate change in river basins, which mainly stemmed from institutional features (2017). On a regional scale, Sietz (2014) improved the reflection of regional nuances of patterns by linking the global patterns of drylands vulnerability to modeled trends of smallholder development in Northeastern Brazil. On the same scale, Sietz et al. identified typical socio-ecological patterns of smallholder farmer vulnerability to weather extremes in the Peruvian Altiplano (2012). They verified the regional pattern analysis with household-level interviews. Sietz et al. also identified typical socio-ecological patterns of farming systems' vulnerability in Sub-Saharan Africa (2017).

The studies show that patterns of vulnerability can be found in the data structure of numerous socio-ecological systems around the world, including HICs, middle-income countries (MICs), low-income countries (LICs), and explicitly rural settings. However, no study has investigated whether patterns exist in an explicitly urban setting. This is an important research gap, because humanity is increasingly becoming an urban species. An explorative and purely qualitative review of local and regional case studies for GEO 4 (Jäger et al. 2007) concluded that vulnerability may have a limited number of typical combinations causes in the RUCF. However, a comprehensive data-driven analysis to investigate this with an established methodology is missing. This dissertation sets out to fill this gap.

The abundant literature on patterns of socio-ecological vulnerability has produced valuable insights and robust results in GEC research. However, it is important to test whether such a methodology and existing results can make a meaningful contribution to related fields of research. Despite the fact that socio-ecological vulnerability has many conceivable links to societal outcomes in other fields of research, such a test is lacking so far. In the context of human security, for example, Kok et al. (2015) have raised the question whether the analyzed patterns of drylands vulnerability increase the understanding and distribution of violent conflict in drylands. Yet whether patterns meaningfully contribute to understanding this link is yet to be determined. At the same time, there is a long-standing scientific debate on whether violent conflict occurs due to 'supply induced' scarcity of natural resources, or mainly due to the socio-economic/political context. Therefore, this dissertation sets out to test whether both the concept and the example of patterns of socio-ecological drylands vulnerability can make a meaningful contribution to an inconclusive scientific and political discourse in human security research.

Although the growing body of literature shows methodological advancements in vulnerability patterns research, some methodological shortcomings are still evident. Firstly, Sietz et al. (2011) applied a methodology *specifically to drylands.* Yet the introduction of a formalized methodology for systematically analyzing typologies of vulnerability in socio-ecological systems *in general* is still missing. This is required for better uptake in the scientific community. Therefore, this dissertation sets out to fill this gap. We choose to provide a proof of concept in drylands for this more generally applicable methodology, because qualitative and quantitative studies on typologies of socio-ecological vulnerability exist for comparing results.

Secondly, cluster analysis is sensitive to a host of indicator characteristics. Characteristics include the choice of indicators, the number of indicators, and the indicator data. Therefore, using cluster analysis in indicator-based vulnerability analysis requires careful treatment of sensitivity. Despite an explorative use of indicator variance (Sietz et al. 2011) a robust basis for investigating the sensitivity of a clustering to each indicator, for example, is missing. This is important for identifying how influential indicators are for the data structure. This dissertation sets out to perform a more comprehensive sensitivity analysis for using clustering for vulnerability pattern research.

What kind of methodological challenges are to be expected, having set these goals for this dissertation? Firstly, a generally applicable methodology needs clear reference to a well-established framework for socio-ecological vulnerability analysis. This is required for better uptake in the scientific community. Secondly, each step of the clustering methodology needs to be explicit and transparent to make the clustering easily interpretable, assessable, and verifiable for the reader.

This includes explicitly treating typical problems with certain clustering algorithms on the one hand, and conducting comprehensive sensitivity analysis on the other. This sensitivity analysis includes sensitivity to starting points of clustering, different pre-assigned amounts of clusters, scaling of indicator data, and leaving out indicator datasets. Finally, even though clustering is a standard method in GEC research, interpreting clustering results requires supporting information to avoid obscuring richness in detail.

1.3 Drylands Vulnerability and Human Security

After the Cold War environmental factors have become a dominant theme in the discourse of human security (Urdal 2005). More recently, the international public policy arena has been paying major attention to the implications of GEC for human security (Kerry 2015; Obama 2009). This attention has also been fueled by a surge of literature on the implications of climate change for violent conflict, e.g. by undermining food security through increasing natural resource scarcity.

A critical societal outcome for human security is violent conflict. Although numerous definitions exist, a commonly used definition of violent conflict in peace and conflict research is ''...a contested incompatibility that concerns government or territory or both where the use of armed force between two parties results in at least 25 battle-related deaths'' (Gleditsch et al. 2002).

There is a long-standing scientific debate whether natural resource scarcity is decisive for violent conflict outbreak (Bächler 2000; Homer-Dixon et al. 1998), or whether the socio-economic/political context is more important (de Soysa 2005; Diehl & Gleditsch 2001). Proponents of GEC causing violent conflict by aggravating natural resource scarcity take on a neo-Malthusian position: Supply-induced scarcity of natural resources makes people more prone to violent conflict (Homer-Dixon et al. 1998). For example, violent conflict has been linked to depletion of naturally scarce water resources through overuse or drought on global (Levy et al. 2005), regional (Hendrix et al. 2012), and local levels (Rettberg 2010). While connections between environmental factors and violent conflict have been analyzed in LMICs at length, there are very few applications of socio-ecological vulnerability frameworks for this purpose, one qualitative and explorative application being in GEO 4 (Jäger et al. 2007).

Quantitative studies in this field of research commonly rely on a comprehensive set of socio-economic factors, resource scarcities, environmental factors, political factors, and linear models to combine them. The studies show an inconclusive picture regarding a general connection between resource scarcity and violent conflict.

In these regards, dryland systems are exemplary for many reasons. These naturally resource-scarce systems are characteristically low in rainfall. They are well studied regarding causes of violent conflict on local, regional, and continental scales. Yet, the question whether scarcity actually does drive violent conflict, or whether other social, economic, and political factors are more important, has not been answered conclusively. Regional studies find weak links between natural resource scarcity and violent conflict regarding drought-related parameters, precipitation or vegetation in Mali, Ethiopia, Kenya, and Uganda (Benjaminsen 2008; Benjaminsen et al. 2012; Meier et al. 2007). Instead, the studies emphasize socio-economic and political factors as the main causes. Other studies find evidence for a connection of violent conflict to high temperature extremes in Eastern Africa (O'Loughlin et al. 2012) and sub-Saharan Africa (O'Loughlin et al. 2014), and wetter conditions in Kenyan Drylands, and Northern Kenya (Adano et al. 2012; Witsenburg et al. 2009). On a general level, temperature increase has been proposed as a driver of violent conflict on a global level (Hsiang et al. 2013, 2011a), for Africa (Burke et al. 2009, 2010), and Eastern Africa

(O'Loughlin et al. 2012). Yet others find weak or no systematic evidence for these links (Wischnath et al. 2014; Buhaug 2010). Again, other factors appear to be important. For example, studies in peace research have found a robust link between socio-economic factors, such as poverty and low rates of economic growth, to violent conflict (Collier et al. 2004; Fearon et al. 2003; Hegre 2006).

At first sight the inconclusive significance of natural resource-based, or socio-economic and political factors suggests that typical narratives to explain violent conflict with these factors do not exist in quantitative studies. All the nuances appear to make it hard to link the societal outcome of violent conflict to its multiple causes. However, the research design of many quantitative studies, and the methods they commonly use, offer various explanations for why the debate is unresolved. Firstly, studies that incorporate both resource scarcity-based and human dimensions to explain violent conflict tend to have dichotomous outcomes: Either one or the other dimension is the main driver. Cause-effect based relationships involving both dimensions are rarely proposed (O'Loughlin et al. 2014, 2012). This rules out integrating both dimensions, e.g. through a socio-ecological framing, for more nuanced explanations for violent conflict onset. Secondly, studies commonly use linear models to combine factors within and between both dimensions, which is a strong and restrictive assumption. This implies that an additional effect of one factor (e.g., poverty, or drought) on conflict probability is independent from the value of another factor (e.g., soil degradation, or government effectiveness). This can obscure the complexity between the societal outcome of conflict and its multifaceted causes, because different relationships between factors may apply under different conditions (Buhaug et al. 2008). Therefore, methods that accommodate for non-linear relationships within and between socio-economic and ecological factors are worth testing, because numerous potential factors appear to nuance violent conflict onset. Thirdly, many studies rely on, or aggregate, environmental, human, and conflict data to the national level (Burke et al. 2009; Hendrix et al. 2012; Magnus Theisen 2008). This obscures any differentiation and distribution of factors on this level, let alone on a subnational level, and suggests using alternative disaggregated methods for a more realistic spatial picture.

Non-parametric methods (e.g. cluster analysis), and concepts (e.g. vulnerability) commonly applied in GEC research accommodate for these three properties (non-dichotomous outcomes, human-environment interactions, subnational resolution), which are commonly lacking in peace research. This motivates testing whether both the methodology for - and our typology of - socio-ecological vulnerability in global drylands can make a meaningful contribution to an ongoing scientific and political debate in human security. We test whether, and where, resource scarcity, overuse, and poverty-related factors - typical problem structures causing drylands vulnerability for smallholder farmers - and their spatial distribution on a sub-national level increase the understanding of what drives violent conflict in drylands. Therefore, some methodological challenges are to be expected. Firstly, spatially explicit high-resolution data on violent conflict in drylands worldwide needs to be secured and pre-processed. Secondly, we need to make quantitative results from our non-parametric method comparable to traditional parametric methods to elicit which one is superior. Thirdly, we need to find qualitative systematic explanations for violent conflict onset in each affected cluster of our drylands typology. Fourthly, we need to plausibilize these explanations with local and regional conflict case studies.

1.4 Rapid Coastal Urbanization

GEO 4 proposed a number of major global socio-ecological systems in which a limited number of causal combinations typically shape vulnerabilities (Jäger et al. 2007). The only system which was strictly urban - the RUCF - is currently a focus of attention in the scientific and political discussions on global urbanization.

Ever since the emergence of the first cities over 6000 years ago, human populations have resided in rural and urban areas. Since 1950, the world has undergone an unprecedentedly rapid urban development. Urban population has since increased by over factor five, from 729mn to 3.9bn (UNDESA 2015). Now, for the first time in history, urban areas are the predominant type of human settlement (Grubler et al. 2012), and currently home to 54% of the world's population (UNDESA 2015). Urban population is projected to increase by 2.5bn until 2050, amounting to 66% of the global population (UNDESA 2015). In the next decades, nearly the entire net global population growth is projected to be in cities in LMICs (UNDESA 2008, 2012). The pace of human settlement growth and population growth in cities has led to the recognition that urbanization is a defining phenomenon of our time (Hoornweg et al. 2011), as humanity increasingly becomes an urban species.

Rapid urbanization occurs heterogeneously, and exhibits patterns. Firstly, urbanization is more rapid on coasts than it is in inland areas (McGranahan et al. 2007; Seto et al. 2011). This is largely attributed to greater economic opportunity: Historically, access to waterways has been advantageous for trade. This explains why cities are disproportionately located along coastlines and rivers (Grimm et al. 2008), and urban areas are generally more coastal than rural areas (McGranahan et al. 2007).

Secondly, rapid urbanization is a phenomenon which is largely at work in LMICs (The World Bank 2010, 2009). The current rapid urbanization of the Chinese seaboard is an illustrative example for this, and considered to be the greatest rural-urban migration in human history (Zhang et al. 2003). However, this rapid pace of urbanization is not unique to China. It is rather a global pattern which is also observable in many other coastal regions, e.g. in Nigeria, Angola, Yemen, Bangladesh, or Thailand (UNDESA 2015).

A patchwork of local and regional case studies provides insights into ongoing discussions about the vulnerability of fast-growing coastal urban areas under multiple socio-economic and environmental problems. However, countless urban areas remain unassessed. Case studies repeatedly show two things:

Firstly, rapid urbanization is contextualized by socio-economic and environmental (i.e. biophysical) factors operating on multiple temporal and spatial scales (De Sherbinin et al. 2007; Jäger et al. 2007). On the one hand, rates and levels of urbanization influence environmental and socio-economic outcomes (Turok et al. 2013): Factors such as unmanaged urbanization (Grimm et al. 2008), urban expansion (Seto et al. 2011), and urban resource demand (Bloom 2011) are radically altering natural coastal environments. On the other hand, some environmental factors affect coastal cities in particular, for example flooding due to tropical storm surges, or sea-level rise (Handmer et al. 2012).

Secondly, studies also show that, under rapid urban growth, these long-standing and emerging factors threaten to outpace vulnerability reduction efforts (O'Brien et al. 2012; UN-HABITAT 2011; UNISDR 2011) by increasing exposures and sensitivities in human systems and ecosystems alike (McGranahan et al. 2007). This is especially the case in LMICs, because of their generally higher vulnerability, and severely limited resources for reducing vulnerability. Therefore, rapid urbanization poses serious challenges for integrated human development and environmental sustainability in LMICs.

There is a lack of global studies which systematically structure problematic combinations of these environmental and socio-economic conditions for human populations under rapid urbanization. The literature gives various reasons as to why addressing this gap is relevant, and important. Firstly, they would allow for formulating vulnerability-reducing responses to different urbanization patterns. For Turok & McGranahan (2013) this would require a holistic approach based on environmental and socio-economic considerations. Secondly, studies focusing on vulnerability are particularly relevant for upscaling: Garschagen & Romero-Lankao (2013) emphasize the greater scientific attention the linkages between different components of vulnerability under urbanization deserve, because they would identify broader vulnerability-reducing measures for national level strategies. Thirdly, establishing a baseline of the current situation is important in view of future urbanization and climate change impacts.

The need for vulnerability analyses as a basis for large-scale vulnerability reduction in fast-growing coastal cities is clear. However, this basis is difficult to achieve with the current modus operandi of local or global studies. On the one hand, local case studies are insufficient as a sole basis for upscaling. At first sight they appear to be a patchwork of distinct vulnerability analyses in unique places. It is challenging to formulate and upscale response options across cities on this basis: This requires focusing on similarities, not uniqueness, in city case studies. In addition, local case studies are incomplete without accounting for global influences. On the other hand, global studies are also insufficient as a sole basis for downscaling, because they lack nuanced insights from local case studies. In contrast to city case studies, global studies of coastal cities understandably resort to an isolated treatment of interrelated socio-economic and environmental problems (Garschagen et al. 2013). Apart from this, rapid urbanization is treated as an indiscriminate phenomenon with little regional and local variation in context (Hallegatte et al. 2013). Therefore, under limited financial and human resources, identifying generic adaptation needs with greater spatial coverage requires integrating local and global insights.

1.5 Research Questions

Motivated by the general introduction and the introductions on vulnerability pattern recognition, violent conflict in drylands, and rapid coastal urbanization, my dissertation seeks to answer the following overarching research question RQ 1:

RQ 1) How can socio-ecological vulnerability of human populations in specific systems with global distribution be reduced in complexity to identify generic local and regional adaptation needs, given the lack of financial and human resources to locally assess all places in need?

In order to answer this research question, my dissertation globally systemizes typical combinations of causes of socio-ecological vulnerability under global change, and shows where they occur. It does this in three major contexts in two socio-ecological systems:

- Drylands
- Human security in drylands
- Fast-growing urban coasts

It does so by identifying causes typically documented in local and regional case studies. Analyzing typical combinations of these causes would increase the understanding of the underlying problem structures of vulnerability beyond individual cases – as long as the typical combinations and their distribution are shown to be plausible through local and regional case studies. This is useful for establishing global overviews of generic vulnerability reduction needs in view of fragmented patchworks of local case studies and a global lack of funding.

This aim leads to the formulation of three major research questions RQ 2 – RQ 4, which were motivated by sections 1.2, 1.3, and 1.4:

RQ 2) How can a spatially explicit methodology used for globally systemizing typical causes of socio-ecological vulnerability of human populations in drylands be refined to be applicable to any socio-ecological system, and how can its application benefit vulnerability reduction?

RQ 3) Does a global typology of typical causes for socio-ecological drylands vulnerability involving resource scarcity, overuse, and poverty-related factors increase the understanding of what drives violent conflict?

RQ 4) What are causal patterns of socio-ecological vulnerability which are typical for urban populations in the context of rapid coastal urbanization, and how are they positioned to deal with these vulnerabilities?

1.6 Dissertation Structure

This section explains the structure of the dissertation based on assigning the research questions, and the analytical approaches to address them, to chapters. Figure 1.1 provides an overview of the structure. Besides assigning chapters and sections to the research questions, it shows which publication has contributed to answering each research question. Chapter 1 ("Introduction and Overview") motivates and poses the research questions (ovearching RQ 1, and RQs 2-4). Chapters 2 (publication "Drylands"), 3 (publication "Conflict"), and 4 (publication "Urban") each consist of one publication as a basis for addressing and answering RQ 2, 3, and 4, respectively. Chapter 5 ("Discussion and Conclusions"), shows how the results from the publications contribute to answering the overarching RQ 1, embeds these results in the current state of scientific knowledge, and shows their added value.

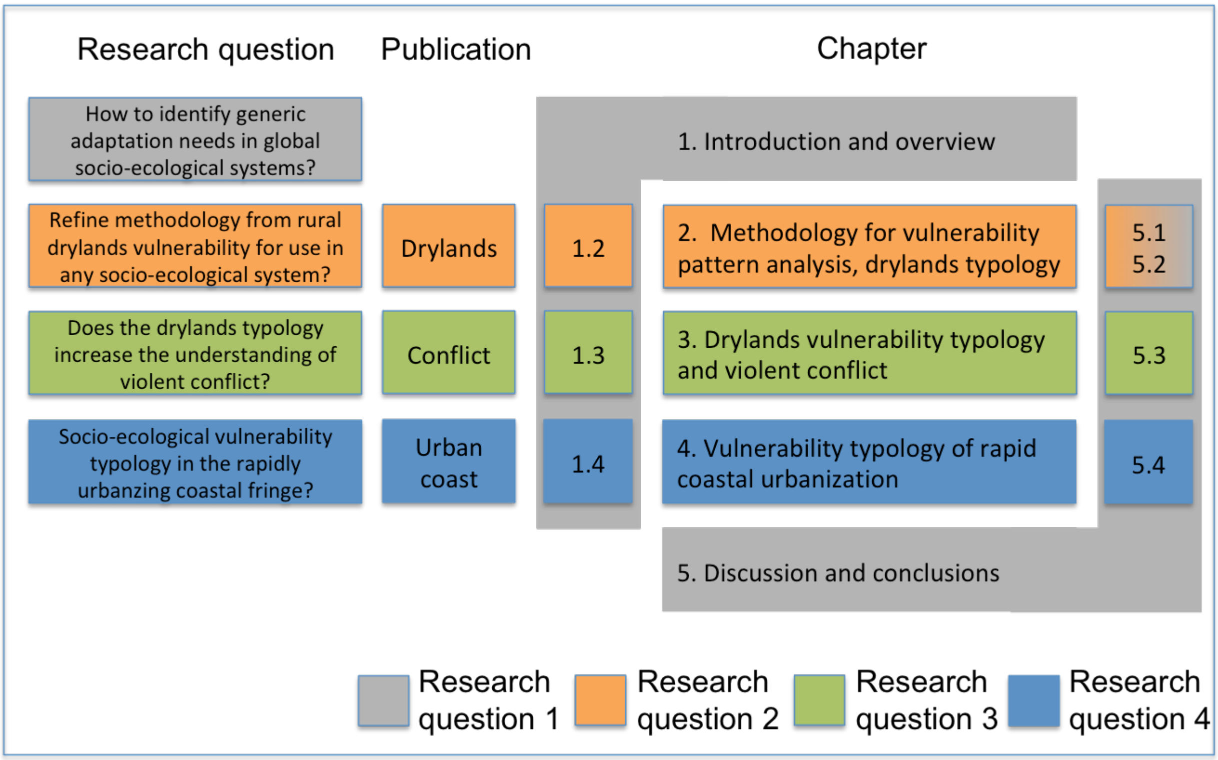

Figure 1.1: Overview of the dissertation structure. Publications and chapters are attributed to research questions. The titles of chapters 2-4 are short versions of the respective chapters.

Chapter 2 (publication "Drylands") addresses RQ 2 by advancing an existing spatially explicit methodology for analyzing socio-ecological vulnerability patterns in global drylands. The methodology was initially used to identify typical combinations of factors causing vulnerability in that specific socio-ecological system, and linked the combinations to where they occur. Chapter 2 formalizes the methodology, and improves the sensitivity analysis, thus making it applicable in any specific socio-ecological system. This increases the potential for scientific uptake of one of the few methodologies for vulnerability analysis, which integrate global overviews and local detail. Second, the chapter describes applications of the methodology for generic vulnerability reduction across places with similar causes. This is useful for scaling up good practices to meet adaptation needs. In a proof of concept, this method is subsequently employed for developing, interpreting, and verifying a robust global typology of drylands vulnerability with subnational data. The obtained typology of drylands vulnerability patterns is plausibilized using studies and case studies (see Annex, Table 8), and employed in Chapter 3 to answer RQ 3. The method is employed a second time in Chapter 4 to analyze a global typology of urban coastal vulnerability under rapid urbanization for answering RQ 4.

Violent conflict is a societal outcome with conceivable links to socio-ecological vulnerability and GEC. Chapter 3 (publication "Conflict") addresses RQ 3 by analyzing the spatial distribution of violent conflict in drylands. It employs the typology of drylands vulnerability from Chapter 2 for the analysis. The purpose of this analysis is twofold: The first purpose is to test whether the global drylands typology resulting from our methodology can contribute to an ongoing discourse in a different field of research, which has conceivable links to socio-ecological vulnerability and GEC. The second purpose is to improve the understanding of the implications of resource scarcity, overuse, and poverty-related factors in drylands for violent conflict. Thereby we aim to contribute to a long-standing debate about whether resource scarcity or socio-economic / political context is decisive for violent conflict incidence. Our method's quantitative explanatory power for violent conflict incidence and distribution in drylands is compared to a conventional linear method from peace research. Characteristics of the typology are plausibilized using local and regional case studies related to resource scarcity and violent conflict in a conflict-intensive drylands sample (see Annex, Table 8).

Chapter 4 (publication "Urban") addresses RQ 4 by employing the method advanced in Chapter 2 in the context of socio-ecological vulnerability in the RUCF. The publication undertakes a comprehensive systemization of socio-economic and environmental problems causing vulnerability of human populations in urban areas in the rapidly urbanizing coastal fringe. The purpose of this analysis is to provide a missing spatially explicit and global overview of typical problems structures which cause urban vulnerability using largely sub-national data. After testing the plausibility of the overview with an ample body of studies and case studies the publication proposes entry points for pattern-based vulnerability reduction.

2 A New Method for Analyzing Socio-ecological Patterns of Vulnerability[1]

Abstract

This paper presents a method for the analysis of socio-ecological patterns of vulnerability of people being at risk of losing their livelihoods as a consequence of global environmental change. This method fills a gap in methodologies for vulnerability analysis by providing generalizations of the factors that shape vulnerability in specific socio-ecological systems and showing their spatial occurrence. The proposed method consists of four steps that include both quantitative and qualitative analyses. To start, the socio-ecological system exposed to global environmental changes that will be studied needs to be determined. This could for example be farmers in drylands, urban populations in coastal areas and forest dependent people in the tropics. Next, the core dimensions that shape vulnerability in the socio-ecological system of interest need to be defined. Subsequently, a set of spatially explicit indicators that reflect these core dimensions is selected. Cluster analysis is used for grouping the indicator data. The clusters found, referred to as vulnerability profiles, describe different typical groupings of conditions and processes that create vulnerability in the socio-ecological system under study and their spatial distribution is provided. Interpretation and verification of these profiles is the last step in the analysis. We illustrate the application of this method by analysing the patterns of vulnerability of (smallholder) farmers in drylands. We identify eight distinct vulnerability profiles in drylands that together provide a global overview of different processes taking place and sub-national detail of their distribution. By overlaying the spatial distribution of these profiles with specific outcome indicators like conflict occurrence or migration, the method can also be used to understand these phenomena better. Analysis of vulnerability profiles will in a next step be used as a basis for identifying responses to reduce vulnerability, for example to facilitate the transfer of best practices to reduce vulnerability between different places.

Keywords: vulnerability, global environmental change, patterns, drylands, indicator-based analyses, adaptation

2.1 Introduction

Many situations of human vulnerability around the world share similar features in terms of drivers and processes that create them. Insights in these similarities emerge from studies on for example land-use change, desertification and deforestation, food insecurity, freshwater scarcity, which show that, in many cases, a small set of key mechanisms explain these situations (Geist et al. 2001, 2004; Misselhorn 2005; Rudel 2005, 2008; Srinivasan et al. 2012). Insight in these mechanisms is important for developing policy responses to reduce vulnerability and facilitate learning across places. In this paper we present a method for systematically investigating these mechanisms across the globe within a given socio-ecological system in a quantitative and spatially explicit manner. This method results in the identification of typical patterns of vulnerability on a global spatial scale. We apply the method to analyze the vulnerability of farmers in drylands to show the potential of this method for identifying options to reduce vulnerability.

[1] This article was published in 2015 in Regional Environmental Change, Volume 16, Issue 1, pp.229–243.

Although there are differences in the use of terminology (Hinkel 2011; Rothman et al. 2014; S. Wolf et al. 2012) most frameworks for vulnerability analysis discussed in the literature distinguish between three components: exposure, sensitivity and coping / adaptive capacity (Birkmann 2013; IPCC 2007; Kasperson et al. 2005; Patt et al. 2008; Schröter, Polsky, et al. 2005; Turner et al. 2003). Factors determining vulnerability to diverse pressures can operate over different temporal and spatial scales and require taking the whole human-environment system into account (Vogel et al. 2004). To capture these various aspects, vulnerability research applies a wide range of methods, stemming from various disciplinary backgrounds and operating on all scales (from local to global). While this great variety of methods and the lack of unified approaches indeed makes it difficult to compare the results of vulnerability studies between different parts of the world or amongst different groups in society (Alcamo et al. 2008; Hinkel 2011, 2009), some frameworks have been proposed to facilitate unified analysis. (Birkmann 2013; Carter et al. 2007; Patt et al. 2008; Schröter, Polsky, et al. 2005; Turner et al. 2003).

One of the reasons that vulnerability studies are difficult to compare, relates to the different spatial scales on which they operate. Often, vulnerability analyses are local case studies that address the usually complex, context-specific situations that shape vulnerabilities of a particular group in a specific socio-ecological situation (Eakin 2005; Sallu et al. 2010; Sietz et al. 2006). The generalization of case studies and their relevance in similar situations elsewhere is always a difficult question. At the other end of the spectrum, global vulnerability assessments are based on aggregated data and rather crude assumptions about the underlying mechanisms being assessed. Even with increasingly finer spatial resolution of global and regional datasets, the question remains whether local specifics can be adequately represented and understood in a global context (Kasperson et al. 2005).

We argue in this paper that vulnerability analysis on an intermediate level of complexity and spatial extent, such as is proposed here in the form of *patterns of vulnerability*, is a useful addition to currently available methods for unifying vulnerability analysis, which range from local (Eakin 2005) to regional (O'Brien et al. 2004) and global (Schröter, Polsky, et al. 2005). Analysing patterns of vulnerability helps to systemize outcomes of case studies with regard to the general, functional processes that shape vulnerability. Furthermore, this analysis does provide both global overviews as well as sub-national detail on the spatial distribution of these patterns. These insights can be used as entry points for developing policy responses to reduce vulnerability in different locations in which similar vulnerability-creating mechanisms play a role, and facilitate learning across places. Furthermore, it renders a useful basis for understanding specific impacts in vulnerable situations, such as the occurrence of conflicts, through for example an overlay analysis (Sterzel et al. 2014) or migration (Neumann et al. 2015).

This idea of analysing *patterns of vulnerability* originates from the fourth Global Environmental Outlook: Environment for Development (GEO 4) published by UNEP (2007). In a response to requests from governments to show how the environment provides challenges and opportunities for human development, UNEP gave the concept of vulnerability a central place. While GEO is a global assessment, its strong regional focus also required going beyond providing coarse global overviews or simple rankings of vulnerability, to find new ways to be sufficiently relevant for countries and regions. From the regional analysis of state and trends in the environment and its impacts on human well-being, seven problem areas were derived in which the vulnerability of people in specific socio-ecological systems was analyzed by looking at the main vulnerability creating processes (Jäger et al. 2007, 318; Kok et al. 2015) These problem areas included the urbanization of the coastal fringe, disturbing the fragile equilibrium in drylands and small island developing states. The analysis of the global dryland was further elaborated in a global study by (Sietz et al. 2011) which identified the spatial distribution of different types of dryland vulnerability.

Building on this analysis, as well as on additional work on patterns of vulnerability in various ecological systems (Jäger et al. 2007), we here present a further elaborated method and apply it to analyze vulnerability of (smallholder) farmers in drylands to show its added value, the methodological issues involved and the insights that can be gained from this type of analysis for policy making. While this paper focuses on the method, related publications apply this method and elaborate in more detail patterns of vulnerability related to forest overexploitation, rapid urbanization in coastal areas (cf. chapters 4 and 6 in Kok et al. 2010) and use the identified patterns of vulnerability to analyze conflict in drylands (Sterzel et al. 2014).

2.2 Rationale for Identifying Patterns of Vulnerability

The above mentioned three components of vulnerability (exposure, sensitivity and coping / adaptive capacity) vary considerably among individuals, different social groups and communities, making human vulnerability to environmental change inherently different for each community or individual. Consequently, vulnerability is the outcome of multiple stressors and multiple actors in multiple contexts that can occur at various spatial and time scales (De Sherbinin et al. 2007; Patt et al. 2008; Schröter, Polsky, et al. 2005; Turner et al. 2003; Vogel et al. 2004). Vulnerability analysis needs to reflect these complex realities.

Comprehensive vulnerability analysis of specific socio-ecological systems could either be provided starting from single case studies or from global indicator-based studies or indices. The synthesis of single case studies towards a more comprehensive overview of vulnerability is often hampered by the diversity and incongruence in approaches employed in the case studies and differences in availability and quality of data. Global overviews are typically falling short in including potentially important local specificities. Between these extremes the approach to identify patterns of vulnerability on an intermediate level of complexity (of mechanisms and conditions) and spatial resolution is an attempt to find a compromise leading to a more comprehensive picture of the major factors involved. Needless to say, this also has to cope with a limited availability of potentially important place-based information on the scale considered (especially for more complex social indicators such as power, politics and voice).

From a formal point of view, state of the art vulnerability assessments on higher spatial scales commonly have index-based outcomes, in which the detail of study is aggregated to one value for each place (Cutter et al. 2003; Kaly et al. 2004; Lonergan et al. 1999; Welle et al. 2013). If vulnerability is reduced to a single composite indicator (index), the richness and complexity of the processes that create and maintain vulnerability is lost, even more so on the large scales of analysis considered (Barnett et al. 2008). That is why it is argued that disaggregated indices are more useful than a single index, as they provide richer information on the structure of vulnerability (Adger et al. 2004). However, this leaves the reader with a multitude of combinations of the disaggregated indices which are not systematically interpreted by the analyst. The pattern approach which we suggest in this paper is the logical next step by asking: can we identify typical combinations of disaggregated indicators and – in case yes – how can they be interpreted in terms of vulnerability generating mechanisms? In doing so we prevent that the resulting vulnerability mapping is obscured by the far-fetched aggregation which is a consequence of working with indexes (Preston et al. 2011).

An existing approach addressing a similar problem of providing generic overviews on an intermediate level is the “syndrome approach”. This approach looks at unsustainable patterns of interaction between people and the environment at a global level, and aims to unveil the dynamics behind them (Lüdeke et al. 2004; Manuel-Navarrete et al. 2007; Petschel-Held et al. 1999). This approach was based on the hypothesis that it is possible to identify a limited number of typical dynamic cause-effect relationships (syndromes) at an intermediate level of complexity which allows to subsume case studies which address relevant environmental problems all over the globe. Srinivasan et al. (2012) recently present an interesting example of analysing and linking 22 human-water system case studies over the globe in terms of a limited number of syndrome configurations. The resulting six syndromes can be explained by a limited set of causal factors falling into four categories: demand changes, supply changes, governance systems, and infrastructure & technology.

While the syndrome approach can be used for analysing separate local and regional case studies, it can also be applied to provide a global mapping, as exemplified in Cassel-Gintz et al. (1997) and Lüdeke et al. (2004) who semi-quantitatively assess the presence of non-sustainable development paths by employing fuzzy calculation rules on basis of globally available indicator-information on factors of interest. This requires a set up in which the various factors of interest are explicitly *hypothesized* to affect vulnerability of human wellbeing towards global- and environmental change in a certain prescribed way, as represented by the (semi-quantitative) relationships employed. An interesting example of a related approach which explicitly postulates a framework to express vulnerability from various (disciplinary) viewpoints, and which also uses fuzzy indicators and calculation rules to build the associated inference models, is delivered by Alcamo et al. (2008).

In our approach we employ a different way to analyze the vulnerability pattern within a well-defined socio-ecological system (e.g. agriculture in drylands). We do not impose a hypothesized predefined relationship, but let the available data on vulnerability mechanisms tell their own story: exploring the structure in the data-space we hope to (inductively) obtain clues on the underlying vulnerability patterns in a specific socio-ecological system worldwide which can be presented on a global map.

2.3 Method for Analysing Patterns of Vulnerability

For analysing patterns of vulnerability within a chosen socio-ecological system it is necessary to answer the following questions:

1. What are the main exposures, key vulnerable groups, their sensitivities and their coping and adaptive capacities?
2. What are the core dimensions of the patterns of vulnerability occurring in the socio-ecological system under investigation?
3. In which regions do we find similar vulnerability characteristics (vulnerability profiles)?
4. What do the different vulnerability profiles signify in terms of vulnerability creating processes?

We propose a method to answer these questions in four steps that will be further elaborated below. It follows a similar logic as the framework of Schröter et al. (2005) for place based studies. To be able to capture the various relevant dimensions of human vulnerability we stress the need to combine qualitative analysis and quantitative tools in applying this method to identify and describe patterns of vulnerability. This needs to be an iterative process as each step provides knowledge that could require the analysis to go back to previous steps. The method offers also opportunities to involve different stakeholders in the analysis.

Step 1 Defining a relevant and distinct socio-ecological system for vulnerability analysis

Question: what are the main exposures, key vulnerable groups, their sensitivities and coping and adaptive capacities in a specific socio-ecological system?

There is no unique or objective way to identify relevant problem areas and socio-ecological systems. Different approaches that could be used are: expert-based, like with the syndrome approach (WBGU 1994); user-driven, such as in the GEO process (Jäger et al. 2007); or through science-policy workshops (Manuel-Navarrete et al. 2007). User-driven approaches will score better in terms of legitimacy of outcomes while expert driven identification may be biased, but efficient in terms of covering the present state of scientific knowledge.

The definition of a relevant problem area and a related socio-ecological system includes an identification of possible exposures, sensitivities and coping and/or adaptation mechanisms, and understanding how well-being of the vulnerable populations may be affected.

Step 2 Identification of core dimensions and indicators

Question: what are the core dimensions of the patterns of vulnerability occurring in the investigated socio-ecological system?

To further specify the socio-ecological system, the variety of mechanisms and processes constituting the vulnerability identified in the previous step needs to be reduced to what we label its 'core dimensions'. This can be either done by referring to existing literature on case study generalizations or by own vulnerability study generalizations, using e.g. the results of meta-analyses (Geist et al. 2002, 2004, Rudel 2005, 2008) or vulnerability scoping diagram (Polsky et al. 2007) to facilitate the comparison of assessments.

Next, indicators need to be identified that render information on the most important dimensions of the vulnerability-creating mechanisms. In principle, these indicators can be taken from all kinds of sources, e.g. survey data, model results, maps (Birkmann 2007, 2013). As we want to understand where the patterns of vulnerability are occurring this requires spatially explicit data as much as possible.

Step 3 Identification of vulnerability profiles and their spatial distribution

Question: in which regions do we find similar vulnerability profiles/situations?

To further answer the question in what form and where typical combinations of the vulnerability – creating processes occur, the selected indicators are subjected to formal data analysis. The outcomes of this step characterize the pattern of vulnerability in two components: (1) a functional component, which are specific constellations of indicators that we label 'vulnerability profiles' (see Figure 1); and (2) a spatial component, which is the spatial distribution of the vulnerability profiles (see Figure 2).

Several techniques for spatial data analysis exist (see Locantore et al. 2004 for an overview). When prior information on the inherent structure of data (in this case the indicator data) is absent or minimal as is usually the case with indicators used at a global level, cluster analysis is a suitable statistical technique to explore such datasets. It groups data into classes – groups or clusters – that share similar characteristics. Here, we use cluster analysis to identify specific constellations, or groups, of indicator values that suggest the different forms in which a pattern of vulnerability can manifest itself.

An important issue when carrying out cluster analysis is the decision on the number of clusters to be distinguished and used in the further analysis. To determine the number of clusters which provides an adequate representation of the internal structure of the data we developed a measure of the stability of the cluster partitions. See Annex A for further details on the clustering method applied.

Step 4 Interpretation and verification of vulnerability profiles

Question: what do the different vulnerability profiles signify in terms of vulnerability creating processes?

The distinct vulnerability profiles resulting from step 3 show typical indicator combinations. Relating this information to the core vulnerability dimensions of the considered socio-ecological system identified in step 2, each vulnerability profile has to be interpreted regarding the characteristic vulnerability generating processes or mechanisms. The spatial distribution of these profiles around the world describes where these different manifestations can be found.

In this interpretation step we analyze what drives the vulnerability in a specific cluster, what explains the differences between vulnerability profiles and whether the locations where a specific vulnerability profile occurs are also observed in reality. To verify the obtained results and interpretations our quantitative analysis needs to be complemented with empirical, 'on the ground' information. This step is important to complement the global, quantitative data with local, 'on the ground' qualitative information (to address concerns raised by for example Carr and Kettle (2009) to adequately reflect conditions on the ground in quantitative global approaches). This can be done by comparing these outcomes with a meta-analysis of case studies or with numerous detailed case studies (see Sietz et al. 2011, Sietz 2014). We refer to this part of the analysis as *'ground-truthing'*, that is, relating the global, quantitative analysis to detailed information that is collected on the ground. This step adds meaning and detail to the analysis that cannot be derived directly from the global analysis and in this way helps to link the global analysis to local realities and thus supports the identification and interpretation of the vulnerability profiles.

2.4 Patterns of Vulnerability amongst Farmers in Drylands

In this section we illustrate the suggested general approach by its application to the socio-ecological system of dryland farming. The analysis shown here is a further development of prior studies of this problem area (Jäger et al. 2007; Kok et al. 2009; Sietz et al. 2011).

Step 1:Defining a relevant and distinct socio-ecological system for vulnerability analysis

Drylands are critical areas with respect to the challenges and trade-offs of improving human development in a fragile environment, with limited natural resources and high risks of overexploitation. Drylands are characterized by low rainfall and high rates of evaporation, occupy 41% of the Earth's land area and are home to half of all people living in poverty (Dobie 2001). Infant mortality rates in drylands in developing countries are relatively high. Most dryland developing countries have a large proportion of their labor force working in the agricultural sector, with smallholder farmers being highly dependent on natural capital and ecosystem services. Land degradation and climate change endanger agricultural production and environmental sustainability.

Step 2: Identification of core dimensions and indicators

Current literature (Geist et al. 2004; Reynolds et al. 2007; Safriel et al. 2005, 2008) suggests that there are typical and common mechanisms at work that establish the vulnerability of smallholder farmers in dryland areas, especially in developing countries. Their vulnerability is characterized by increasing pressures on the natural resources from a growing population, limited and insecure access to water and fertile soils, and soil degradation resulting from overuse, combined with the breakdown of traditional coping mechanisms, barriers to alternative livelihoods and consequently threatened human well-being. Poor infrastructure impedes market access and, thus, the ability to obtain inputs to enhance agricultural productivity and possibilities for selling products. All these factors may lead to situations in which rural households become enmeshed in poverty traps.

Major vulnerability generating processes are summarized by Reynolds and colleagues (Reynolds et al. 2007) into five key variables important for the "Dryland Development Paradigm", comprising high variability in rainfall (typically occurring in low precipitation areas), low soil fertility (small amounts of organic matter imply that tillage and grazing can quickly have major impacts), sparse populations (not in contradiction to high relative population growth), remoteness (e.g. from markets) and distant voice and remote governance (spatial and social distance from the centers and priorities of decision making). As a result, Reynolds and colleagues show that dryland populations tend to lag behind populations in other parts of the world in terms of a variety of economic and health indicators with higher infant mortality, severe shortages of drinking water and much lower per capita incomes.

The "Dryland Livelihood Paradigm" (DLP) further refines the "Dryland Development Paradigm" taking into account specifically the poverty-degradation spiral (Safriel et al. 2008). The DLP suggests two major alternative development paths. The first path encompasses two branches. One branch describes the overuse of natural resources driven by demographic and socio-economic stimuli leading into poverty, conflicts and violence. The other branch shows that even the sustainable use of resources may result in low human well-being due to the inherent marginality, ultimately inducing the same adverse effects on human well-being as shown in the former branch. In contrast, the second path involves also social and technological ingenuity which stimulates innovations and sustainable use of resources and/or transition to alternative, land-independent livelihoods which altogether stimulate sustainable development (see also Mortimore 2009).

On the basis of this analysis we identify five core dimensions that describe the patterns of vulnerability in drylands. In this description of vulnerability *human well-being* is dependent on available *natural resources* (soils and water), that may be negatively influenced by *pressures on resources*, and their potential *overuse*, resulting in degradation (Dregne 2002b). The latter creates a negative feedback on agricultural production and income generation (e.g. Safriel and Adeel 2008), while *connectedness* illustrates dependence of income generation on "soft and hard infrastructure" (e.g. Shiferaw et al. 2008) which – together with the available capital - also influences the improvement of agricultural techniques (Thomas 2008; Twomlow et al. 1999).

To describe these core dimensions we have selected a set of seven global indicators (see Table 1). Pragmatic reasons as availability and quality of information for global (drylands) coverage and sub-national resolution have played a role in the ultimate choice of the indicators. As we intend to develop this method further in future work for the analysis of alternative scenarios, we have opted to use indicators derived from integrated assessment models, i.e. environmental indicators are related to the IMAGE model (Bouwman, Goldewijk, et al. 2006; Stehfest et al. 2014), and indicators on human well-being and development are related to the GISMO model (Hilderink and Lucas 2008).

Table 2.1: Core dimensions addressed, main variables and indicators and proxies used.

Core dimension	Variable	Indicator	Proxy	Source
Human well-being	Income	Average per capita income	GDP per capita	(UNSTAT 2005; The World Bank 2006)
	Distribution of income	Infant mortality	Infant mortality rate	(CIESIN 2005)
Pressure on resources	Demand for water	Population density	Population density	(Klein Goldewijk et al. 2010)
Connectedness	Soft and hard infrastructure	Infrastructure density	Road density	(Meijer and Klein Goldewijk 2009)
Natural resources	Water supply	Renewable water resource	Surface runoff	(Alcamo et al. 2000)
	Soil quality	Agro-potential	Productivity of grassland compared to the max feasible	(Bouwman, Goldewijk, et al. 2006)
Overuse	Soil overuse	Soil erosion (through water erosion)	Water erosion index	(Hootsman et al. 2001)

As a component of *Human Well-being*, income allows farmers to fulfil their needs and acquiring production enhancers. As for income no gridded data is available, we use country-level income data for all grid-cells within a specific country, supplemented with the infant mortality rate on the sub-national scale, as a proxy that gives some insight into the distribution of income. In case of a sufficient national average of GDP per capita, a high infant mortality rate suggests a very unequal distribution. With respect to *natural resources*, soil quality and climate conditions can be directly indicated by measuring agro-potential. For this we use productivity of grassland compared to the maximum feasible natural productivity in perfect circumstances as a proxy. Furthermore, water availability is indicated by the water runoff per river basin. *Pressure* on these natural resources is indicated by the population density. To indicate *overuse* we use water erosion, which is the most important cause for soil degradation around the world, represented by the water erosion index, i.e. the sensitivity to water erosion in a qualitative sense. Finally, *connectedness* or access to soft and hard infrastructures is indicated by infrastructure density, which is total length of roads per square kilometre.

Step 3: Identification of vulnerability profiles and their spatial distribution

This step identifies in which areas we find similar vulnerability profiles. Cluster analysis is used to identify typical indicator value combinations in the multiple indicator data-space. The optimum number of clusters is determined by investigating the stability of calculated cluster partitions under different initial conditions (see Annex A, figure A1a). The absolute maximum is for three clusters which mainly shows a divide between developing countries and developed countries; a plausible result, which however does not add much new information to our understanding. A richer interpretation comes from the relative maximum at 8 clusters, which hints at an inherent property of the structure in the indicator space. However, even not exactly knowing the optimum number of clusters would not be a severe problem in this case, as the *'branching diagram'* in Annex A (figure A1b) shows. This diagram suggests how clusters split up or merge when increasing or decreasing the number of clusters considered. Using a smaller cluster number than 8, implies that the picture becomes less differentiated, i.e. clusters are mainly merged by going to smaller cluster numbers.

At this point, the question may arise as to whether or not there is a ranking in the importance of single indicators in generating the cluster separation. The *'Fraiman measure'* as depicted in Annex A (figure A1c) shows that the average income is the most important variable for cluster separation, followed by agro-potential and soil erosion; infant mortality and water availability have still some importance. Even though the ranking is led by an economic variable, it is an almost equal mixture of socioeconomic variables, natural conditions, and variables that all characterize the intensity of resource-usage.

The eight clusters define different typical vulnerability profiles, i.e. combinations of indicator values that characterize specific vulnerabilities in different dryland areas (see Figure 1). Although these vulnerability profiles are characterised by the (normalized) cluster centres, there can be significant variation for specific indicators around these average values that can be helpful in characterizing and interpreting these clusters in terms of specific features of the variables considered. Box-plots serve this purpose as they indicate next to the cluster centres also high and low percentiles of the data (see Annex A, Figure A1d), with a small spread indicating that these indicators are relatively distinctive when comparing various clusters. The spatial distribution of these profiles is provided in Figure 2, which clearly shows that six of the vulnerability profiles relate to drylands in developing countries.

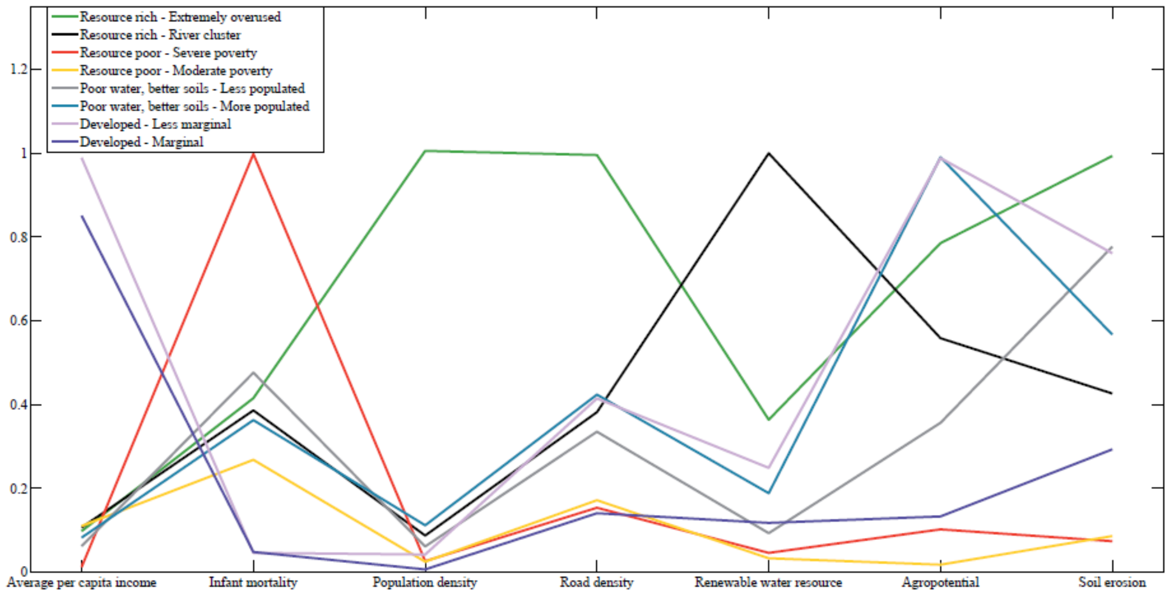

Figure 2.1: Eight typical vulnerability profiles in drylands worldwide. The lines show the average indicator values (i.e. the cluster centres) of the respective cluster. These average indicator values have been normalized between 0 and 1 using their minimum and maximum values over the different clusters, and thus show relative differences of the average indicator scores rather than their absolute differences. The line colours match the colours used in Figure 2 depicting the geographical distribution of the clusters.

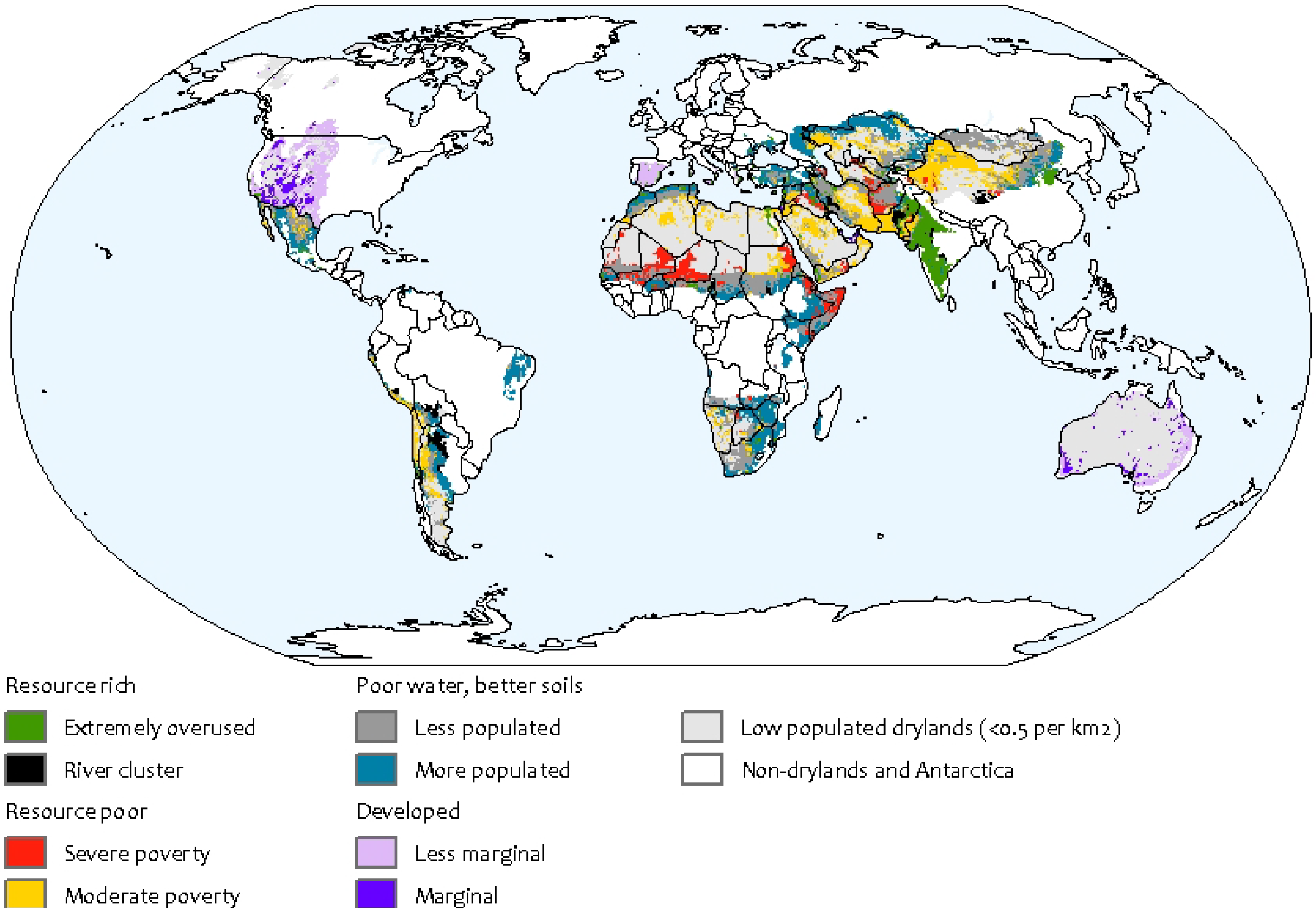

Figure 2.2: Distribution of the eight vulnerability profiles for farmers in drylands worldwide. If for example droughts increase dryland farmers in these different areas become more vulnerable for different reasons. For the respective vulnerability profiles see Figure 1. Low populated dryland areas (less 0.5 per km^2) have been excluded for analysis since representative indicator information on the human-environment interaction for these areas is less reliable.

Step 4: Interpretation and verification of vulnerability profiles

In this step the vulnerability profiles are interpreted and their plausibility is tested by comparison with other related information, as e.g. independent global maps, single local case studies falling spatially within a specific cluster area and meta-analyses. This leads to better understanding of the processes hypothesized by the profiles and to partial verification of their spatial distribution.

The two *developed clusters* (dark lilac-marginal and bright lilac-less marginal in Figures 1 and 2) occur in industrialised countries and show high values for average income and very low infant mortalities. The main difference between the two clusters lies in the difference in agro-potential (factor 7), which might be linked to higher values of road (factor 3) and population (factor 7) density in the less marginal developed cluster (see bright lilac line in Figure 1). In addition to the better agro-potential, the amount of available water is also higher, both of which could motivate more intensive agriculture that potentially generates significant soil erosion. The dark lilac-marginal cluster with agro-potential and amount of available water worse than the bright lilac-less marginal cluster, has only 14 % of the population density compared with the bright lilac wealthy cluster, and related to that, a lower road density. Nevertheless it still has a noticeable soil erosion rate, suggesting soil overuse. Both clusters and their separation are rather robust as their box-plots (Figure A1d) show relatively small variation for most indicators and those indicators that distinguish their partition most show only little overlap when comparing both clusters. With respect to their geographical distribution, these two clusters comprise the arid areas of the OECD countries – according to the dryland definition used here – mainly in the US, Spain, Italy and Australia. Comparison with maps on irrigated cropland (Siebert et al. 2005) and livestock production systems (Steinfeld et al. 2006), shows that the significant soil erosion of the bright lilac cluster correlates with a high percentage of irrigated cropland, whereas the somewhat lower erosion in the dark lilac cluster is mainly associated to overgrazing. Comparison of these cluster results with the meta-analysis study on dryland degradation (desertification) by Geist and Lambin (2004) may serve as an example of verification. From the systematic evaluation of a large number of case studies on desertification processes all over the world they concluded that for Europe most of the case studies report agricultural activities as proximate cause for dryland degradation (share of cropping: 77%). For Europe the cluster analysis identifies almost exclusively the bright lilac cluster where high soil degradation is related to intense crop farming which fits the Geist and Lambin findings. Furthermore they obtain for the USA and Australia that the majority of the case studies report agricultural activities as proximate cause, but here livestock dominates with 83% over cropping with 17% (USA) or has an equal share (Australia). The cluster analysis reproduces this observed situation by identifying a mixture of the bright lilac and dark lilac cluster for both countries, the latter indicating the less fertile and overused rangelands.

The *resource-poor* vulnerability profiles (red and yellow in Figures 1 and 2) identify the most resource-constrained and isolated areas of the world, indicated by the lowest renewable water resources and agro-potential. The harsh dryland conditions might explain the still relatively low levels of soil degradation, as agricultural and grazing practices are not favoured. The very limited renewable water resources pose the risk of unreliable supply. The two profiles differ mainly in level of human well-being (income and infant mortality). Also here, both clusters and their separation are rather robust. Their box-plots (Figure A1d) show very small variation for the indicators and the infant mortality rate, the most distinct indicator for the two clusters, shows no overlap for the 5^{th} to 95^{th} percentiles. Severe poverty occurs in areas dominated by pastoral land use (red cluster: GDP/cap: 11%, Infant Mortality Rate: factor 4 compared to the yellow cluster). This cluster is, e.g. identified in Somalia, described by a case study of Le Sage and Majid (2002). In this region, despite some improvements in access to natural resources and security, the ability of people to recover and stabilize their livelihoods is very limited. The poorest people there are not able to benefit from occasionally better rainfall due to the depleted asset base and war-related constraints to access productive resources. Even though better situated people may produce more crops, debt repayment and recurrent droughts continue to exhaust their livelihood assets. In the yellow cluster, mainly located in the old world's dry belt, Mexico and the North of Chile/Argentina more moderate poverty occurs in zones between pastoral and sporadic, sparse forms of agriculture on the desert fringes and in areas where national economies allow for improved living conditions, for example, because of fossil-fuel exploitation in northern Africa and Saudi Arabia.

The *poor water, better soils* vulnerability profiles (grey and blue in Figures 1 and 2) are less agro-constrained, indicated by medium to high agro-potential, and high soil degradation. The two clusters differ mainly in agricultural conditions and population density which is twice as large for the blue cluster. This is a small absolute difference which, however, is important: more favourable agricultural conditions are combined with proportionally higher population densities while poverty levels are similar, as expressed by infant mortality levels. For both clusters, the box-plots (Figure A1d) show small to medium variation for the indicators (width of 50%-box around the median from 0.08 to 0.3). Furthermore, except for the agro-potential, the 5^{th} to 95^{th} percentiles largely overlap for the two clusters. This makes agro-potential the most important single indicator to distinguish these two clusters. The two vulnerability patterns are found in parallel areas, e.g. neighbouring deserts and the less populated areas close to the desert. The blue cluster is identified for rural areas of East Ethiopia and the Makueni District in Southern Kenia. For both regions detailed case studies exist which can be used for validation. According to Kassahun et al. (2008) rangeland degradation in East Ethiopia has increased in severity and magnitude since the 1970s, resulting in widespread erosion, compaction and salinization of soils. Overgrazing and overexploitation of woody plants further accelerate the pace of soil degradation. Water bodies were also affected by agricultural activities. In the past, rivers were increasingly diverted, which resulted in diminished accessibility in water resources for domestic use and livestock production. This ongoing overuse of natural resources induces declining agricultural yields and generates conflicts over grazing areas and water resources. As a result, food insecurity and increased poverty is observed. This case reflects the overuse of an acceptable agro-potential by an increasing population resulting in poor human well-being as described by the blue vulnerability profile. The same holds for Makueni (Southern Kenia) where Ifejika Speranza et al. (2008) report the combination of low human well-being and high soil degradation under population pressures. Croplands in the Makueni district are heavily degraded since soil and water conservation measures are rarely applied. Together with the unreliable rainfall being characteristic for drylands and partly infertile soils, food production is difficult to be secured. The resulting food insecurity translates into a limited human well-being.

The *resource rich vulnerability profiles* (green and black in Figures 1 and 2) are characterized by better natural conditions. Both vulnerability profiles are least agro-constrained (highest agropotential) while human well-being (average income and infant mortality) is comparable to the poor water, better soils profile. Here, soils have been extremely degraded by a very dense population, also putting future generations under increased pressure. This profile dominates the arid areas of India, but is also found in north-eastern China and on the African Mediterranean coast. A good illustration for the Indian occurrence of this cluster is the case study of Ram et al. (1999) describing the situation in Khabra Kalan (Rajasthan). It shows the relation of increasing population, shrinking land holdings and shortfall of food on small farms which results in the deterioration of the land productivity.

The river vulnerability profile (black) shows moderate agro-constraints and is best endowed with water resources. Furthermore, soil degradation here is moderate compared to the other patterns. This profile combines relatively high income levels with relatively high infant mortality compared to other developing countries, suggesting a very uneven distribution of income opportunities, probably due to differences in access to irrigation and grassland and services like health and education. This is related to the distribution of income; the on average good natural resources may be distributed unequally amongst the population. For the Balochistan part of the Indus basin belonging to the black cluster, Mustafa and Qazi (2007) results agree with the conclusions drawn from the vulnerability profile by showing how the transition from a sustainable, traditional irrigation system ("karez") to groundwater pumping leads to increasing social disparities and degradation of environmental resources. This profile is found around the lower reaches of the Indus, Euphrates, Tigris and Volga rivers, and in other irrigation areas, such as around the Aral Sea. Both clusters show relatively large variation in their indicator values (Figure A1d), while for the indicators that are most characteristic for the two clusters (population density in the green cluster and renewable water resources in the black cluster) their 5th to 95th percentiles almost do not overlap with the other clusters.

2.5 Potential for using Patterns of Vulnerability for further Analysis and Policy Applications

Logical questions to ask at this point are what the added value of this approach is and how it can serve policy making in addressing and reducing vulnerability. Next to contributing to improved understanding of vulnerability in specific socio-ecological systems, we suggest that patterns of vulnerability can be used in at least three different ways: as a basis for identifying specific responses to reduce vulnerability; to identify opportunities for transferability of local approaches for reducing vulnerability to other places; and as a basis for overlay analysis with information on other issues to obtain novel insights on the possible interrelatedness of these issues with dimensions of vulnerability. We briefly elaborate these below.

Basis for analysing response options

Response options are usually either very place specific or identified at a generic level (GTZ 2009; Jäger et al. 2007; Mortimore 2009) for examples in drylands. But using the vulnerability profiles identified with the proposed method, specific places and contexts can be further related to response options. As illustration we here elaborate cluster-specific policy options for some of the vulnerability profiles obtained for the dryland case in section 4.

In the 'poor-water, better-soils' clusters, the soil degradation rate is relatively high and endangers future yields. This can be avoided by the implementation of more sustainable resource management options. For an extensive list of concrete measures see Dixon et al. (2001). The cluster results imply that the more critical resource situation in the grey cluster, reflected by almost solely pastoral use, leaves fewer possibilities to improve productivity by innovative agricultural techniques than in the better endowed blue cluster. This makes it less probable to improve human well-being for the existing population in the grey cluster on the basis of agricultural production. As a consequence, either non-agricultural off-farm labour has to be developed and/or provided. In the blue cluster with better agro-potential, the chance of improving quality of life by more sustainable resource management seems an interesting option, together with limited population density growth. In-migration from less endowed regions, such as the grey areas, could endanger this opportunity if the implication from the comparison of the poor water, better soils clusters holds that population density tends to increase until living conditions become unacceptable.

In the two resource-scarce clusters, the opportunities provided by the natural resource base are inherently very weak. Comparison of the red and yellow clusters reveals that, for the present population density, even a somewhat better agro-potential does not contribute to more wealth suggesting that other national economic conditions are much more important. So, assuming the cluster analysis catches the most relevant factors, moving away from agriculture as main source of income seems here to be the only economically and environmentally sustainable solution.

The same is the case for the overuse cluster. The critical state of intensive agricultural overuse that generates only a very small income from relatively good natural resources due to the high population density can hardly be stabilised by new agricultural practices only. At the same time, pressure on productivity here has to be reduced and ecosystem restoration becomes an option. The natural conditions would then turn into an opportunity for sustainable livelihoods.

Transferability

Patterns of vulnerability allow local policymakers to recognize their specific situation within a broader context of similar situations, providing regional perspectives and important connections between regions, as well as the global context. The method can in this way also be used to identify potential for transferability of policy interventions which were successful in one place to another location. This can be assessed on the basis of the vulnerability profiles, as they identify locations of similar context and problem structure suggesting a similar response to a particular intervention.

Herwig and Ludi (1999) compared the response of seven agricultural plots in the highlands of Ethiopia and Eritrea regarding their response to five different soil conservations measures. Three of these plots are located within the dryland mask, two belong to the grey cluster (poor water, better soils, less populated) and one to the blue cluster (poor water, better soils, more populated). One conservation measure ("grass strip") was tested in all three locations showing a clear difference in erosion reduction between the "grey" cases (-77± 4%) and the “blue” case (-55%). Three further conservation measures showed significant responses and allow for pairwise comparison of the two clusters, all resulting in a much stronger reduction of soil erosion rate for the grey cluster locations, in one case even a strong increase in erosion for the blue cluster location was observed. This is a hint that cluster membership is helpful to understand the success of mitigation measures which were helpful in some locations belonging to a specific cluster.

Given the limited amount of resources available to reduce vulnerability, the identification of similarities may provide additional information necessary for ensuring targeted and more effective interventions. In doing so one should however take care not to overlook local conditions and contexts which can be essential for improving the well-being for the vulnerable people involved (Tschakert 2007).

Overlay analysis

The question arises whether vulnerability profiles and their spatial distribution are useful for analysing other societal outcomes which the vulnerability creating mechanisms can have implications for, yet are not included in the profiles. This question can be addressed by functionally and spatially relating the profiles to geo-referenced outcomes with established or conceivable links in the literature, such as violent conflicts Sterzel et al. (2014). In this way potential policy-relevant underlying causes or circumstances that support or reduce these outcomes can be identified or verified.

Aiming at testing this approach, Sterzel et al. (2014) investigated to what extent the typical profiles of the natural and socio-economic factors which characterize the vulnerability of drylands population to global environmental change presented in this paper are also relevant for explaining the spatial distribution and proneness of violent conflicts of the respective socio-ecological system. They found that conflict incidence in global drylands is heterogeneously concentrated according to the identified typical profiles of socio-ecological vulnerability. Then they show why this intrinsically non-linear approach displays measurable added value over commonly used mono- and multivariate regression model-fits for explaining conflict distribution and proneness in a specific area.

2.6 Discussion and Conclusions

In this paper we have presented a method for identifying typical patterns of vulnerability within a given socio-ecological system. Furthermore, we have illustrated the use of the method by analysing the patterns of vulnerability of farmers in drylands, providing a global overview and sub-national detail. We have also provided how this method could be used for further analysis and policy application.

The core of the method is an indicator-based analysis of a specific socio-ecological system. Cluster analysis is used for analysing indicator data and complemented with verification using (meta-analysis of) available independent case studies and maps. The resulting clusters are distinct and robust combinations of indicator values which are referred to as vulnerability profiles. Vulnerability profiles could be interpreted in terms of the main vulnerability-creating processes that make people in specific situations vulnerable. Furthermore, the cluster partitioning algorithm pinpoints these clusters to specific locations (spatial distribution) and thereby shows where specific appearances of a pattern of vulnerability take place. The vulnerability profiles provide an entry point for identifying opportunities to reduce vulnerability and directions for policy making. Positioning our method into the framework suggested by Schröter et al. 05), it is clear that for materializing our method, we have to build on insights – concerning core dimensions and vulnerability mechanisms of interest – obtained from place-based vulnerability studies performed by others. With a view on furthering the 'public good' of additional insights through cross-study comparisons of research projects designed with common principles, it is clear that the methodological steps in our method are very much aligned to those presented in Schröter et al. (2005).

As the method is not only used to analyse drylands, but also to analyse patterns of vulnerability in relation to 'rapid urbanization in coastal areas' and other socio-ecological systems such as over-exploitation of tropical forest (see chapters 4 and 6 in Kok et al. 2010), we suggest that this new method can provide relevant insights to various human-environment systems where 'specific, representative patterns of the interactions between environmental change and human well-being' are occurring. This does not need to be restricted to global overviews, but may also be applied on a regional or country level. This would also increase opportunities to involve stakeholders in the analysis (for a first attempt see Sietz et al. (2012)).

Reflecting scale-dependent opportunities, working at the global level limits verification efforts due to constraints in globally available observational data. Global data sets should therefore be further developed to provide data which reflect well the spatial and temporal differences in vulnerability outcomes in order to support a more rigorous validation for this type of study. In contrast, applying the method at the local level might facilitate to verify outcome-based aspects of the vulnerability profiles due to better data availability. For example, a study of smallholders' vulnerability in the Peruvian Andes shows the clear correlation between the identified patterns of vulnerability and an independent data set of reported differential vulnerability outcomes in a post-event situation. This relation highlights the relevance of the identified clusters for decision-making processes (Sietz et al. 2012). This kind of verification complements studies that test the consistency of indices of vulnerability against independent data sets of observed or perceived vulnerability outcomes, e.g. in this study, or (Alcamo et al. 2008; Fekete 2009).

A number of considerations need however to be taken into account in applying and further developing this method:

- Data requirements may form an impediment to applying this method (indicator selection and verification of results), as global indicator data are not always available for all the processes that constitute a pattern of vulnerability. This is especially the case for socio-economic indicators such as power, politics and voice, that are often at the root of communities' vulnerabilities.

- In addition to indicator selection, stakeholder involvement may help explain important causes for differences in underlying processes to support the interpretation and verification of the vulnerability patterns. For example, smallholders reported causes of climate vulnerability which deliver rich details that verify and improve the understanding of particular mechanisms in the local context of the Peruvian Andes (Sietz et al. 2012).
- To be able to link vulnerability profiles to the identification of possible policy responses, further meta-analysis of case studies is necessary that establishes the link between vulnerability profiles and the portfolio of opportunities and policy options, their comparability and the possibilities of transferability in a way that also adequately reflects local to regional heterogeneity. One way forward is to link global vulnerability patterns in a spatially explicit way with regionally relevant processes such as shown by an integrated assessment that refines global insights and related options to reduce smallholder vulnerability in Northeast Brazil by combining cluster-based and dynamic modelling approaches (Sietz 2014).
- Application of this method does not directly render information whether certain clusters are more vulnerable than other clusters. Still, to get some insights into how vulnerable a certain cluster is, different rankings of the clusters on single indicator values can provide additional insights on relative risks. Here overlay analysis can be useful, as is indicated by the overlay of the dryland analysis with conflict data by Sterzel et al. (2014) because data with poor spatial coverage can be related in the study afterwards and complement the picture of vulnerability obtained thus far.
- The consequences of alternative policy scenarios for vulnerable groups can be analysed, using global integrated assessment models. This would require extending the cluster analysis into the future by using scenario data from these models (see Lüdeke et al. (2014) for an initial attempt to explore this idea further).

The proposed method for analysing patterns of vulnerability contributes to a better understanding of important processes that constitute risks in similar situations. It shows the spatial distribution of these patterns at the sub-national level, due to the use of geographically explicit indicators. Moreover it can be helpful in strategic thinking about opportunities, responses and policies to reduce vulnerability. Insight into these basic processes that constitute risks can help decision making to set priorities how to reduce vulnerability and enhance development efforts.

Acknowledgements

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3 Armed Conflict Distribution in Global Drylands Through the Lens of a Typology of Socio-ecological Vulnerability[2]

Abstract

Motivated by an inconclusive debate over implications of resource scarcity for violent conflict, and common reliance on national data and linear models, we investigate the relationship between socio-ecological vulnerability and armed conflict in global drylands on a subnational level. Our study emanates from a global typology of smallholder farmers' vulnerability to environmental and socioeconomic stresses in drylands. This typology is composed of eight typical value combinations of variables indicating environmental scarcities, resource overuse, and poverty-related factors in a widely subnational spatial resolution.

We investigate the relationships between the spatial distribution of these combinations, or vulnerability profiles, and geocoded armed conflicts, and find that conflicts are heterogeneously distributed according to these profiles. Four profiles distributed across low- and middle-income countries comprise all drylands conflicts.

Comparing models for conflict incidence using logit regression and ROC (Receiver Operator Characteristic) analysis based on (1) the set of all seven indicators as independent variables and (2) a single, only vulnerability profile- based variable proves that the non-linear typology-based variable is the better explanans for conflict incidence. Inspection of the profiles' value combinations makes this understandable: A systematic explanation of conflict incidence and absence across all degrees of natural resource endowments is only reached through varying importance of poverty and resource overuse depending on the level of endowment. These are non-linear interactions between the explaining variables. Conflict does not generally increase with resource scarcity or overuse. Comparison with conflict case studies showed both good agreement with our results and promise in expanding the set of indicators.

Based on our findings and supporting literature we argue that part of the debate over implications of resource scarcity for violent conflict in drylands may be resolved by acknowledging and accounting for non-linear processes.

Keywords: Socio-ecological system, cluster analysis, subnational resolution, non-linear, resource scarcity, environment

3.1 Introduction

There is a long-standing debate on the role of natural resource factors in explaining violent conflict, spanning from the position that conflicts occur due to 'supply induced' scarcity of resources, particularly renewable resources (Bächler 2000; Homer-Dixon 1999; Homer-Dixon et al. 1998) and the view that mainly the socio-economic/political context is decisive for generating violent conflicts (Brauch 2003; de Soysa 2005; Diehl et al. 2001).

Continuing this contestation, the same inconclusive yet advancing debate is reflected in the recent surge of literature on in how far elements of a broadly defined climate variability can contribute to causing violent conflict by increasing resource scarcity (Buhaug et al. 2008; O'Loughlin et al. 2012; J. Scheffran et al. 2012). Some studies make causal associations of recent global scale climate variability (Hsiang et

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al. 2011b), regional warming in sub-Saharan Africa (Burke et al. 2009) and observed rainfall deviations in Africa (Hendrix et al. 2012) to violent conflict, while other studies find no or only weak links (e.g. Buhaug 2010, Salehyan 2008) or, again, put emphasis on social context (e.g. Benjaminsen et al. 2012). Scheffran and Battaglini (2010) review regions and systems that may be particularly vulnerable to climate change induced resource scarcity. These links, contested or not, commonly are from or relate to drylands regions.

So far it seems clear that studies which particularly focused on a single indicator, such as water scarcity, as a source of conflict have generally not been able to find definitive evidence in support of the environmental scarcity arguments (Benjaminsen 2008; Meier et al. 2007; A. T. Wolf 1999).

Besides the question which variables are assumed to explain conflict occurrence it is important how they are combined. For example, several statistical ("large-N") studies on violent conflict occurrence (e.g. Levy et al. 2005) rely on a comprehensive set of explaining variables (socio-economic factors, resource scarcities, environmental factors, political factors, etc.) but commonly use linear models to combine them. This implies that the additional effect of variable B (e.g. a socio-economic factor) on conflict probability is independent from the value of variable A (e.g. an environmental condition), which is a strong and restrictive hypothesis. One possible reason why the above mentioned debate is still unresolved is that explaining variables' influences on conflict may depend on non-linear combinations of their values: different relations might be valid under different conditions.

Another important reason is the spatial resolution of the explaining variables and the conflict data. A growing number of recent studies emphasize the need to use less aggregated, subnational data (Buhaug 2010; Burke et al. 2010; Raleigh et al. 2006; J. Scheffran et al. 2012). While this is facilitated by the increasing availability of geo-referenced databases of conflict locations for Africa (Hendrix et al. 2012; Melander et al. 2011; Raleigh et al. 2010), studies linking that data to subnational independent variables are still relatively sparse. The body of empirical research for investigating links between debated causes of conflict and the conflicts themselves largely applies country level analyses, likely masking subnational variations (Blattman et al. 2010; Levy et al. 2005). While nationwide values for some socio-economic and policy-related variables, such as for GDP/cap, may be adequate, this may be insufficient for bio-physical data and other socio-economic and policy data.

Motivated by the observations above, this paper applies a typology of smallholder farmer vulnerability in global drylands from Kok et al. (2015, 2010) to empirically assess the possible connection between environmental conditions, poverty related factors, and violent conflicts. The typology from Kok et al. (2015, 2010) resulted from clustering almost exclusively subnational, spatially explicit datasets of key biophysical, resource-related, and socioeconomic factors that were considered most important for generating drylands vulnerability and is thereby an intrinsically non-linear approach. We investigate in how far these typical combinations of natural and socio-economic factors which characterize the vulnerability of drylands population to global environmental change (Geist et al. 2004; Jäger et al. 2007; Reynolds et al. 2007; Sietz et al. 2011) are also relevant for the spatial conflict distribution and conflict proneness of the respective socio-ecological system.

Besides this methodological innovation such a study could generate some general conclusions about the drylands vulnerability-conflicts nexus. The applied drylands typology concentrates on socio-economic and environmental factors where data with global coverage and widely subnational resolution was available. Next to these socio-economic and environmental factors the literature shows that political factors are also important for driving violent conflict (Buhaug Halvard Theisen 2010; Salehyan 2008; Lata 2003). These include, for example, political marginality (Adano et al. 2012; Raleigh 2010), inconsistency of political institutions (Gates et al. 2006; Hegre 2006) or political instability (Fearon et al. 2003).

Acknowledging this restriction with respect to political factors, and in the case of significant relations between conflict occurrence and drylands vulnerability type our approach will allow us nonetheless to contribute to the discourse on the role of environmental factors in conflict explanation by investigating whether there are a) different typical combinations of values of socio-economic and environmental factors with conflict incidence in drylands, b) systematic relationships ***between*** these factors that explain conflict distribution and (non-)incidence, and c) measurable advantages of this approach over commonly used linear fits. On the condition that these points apply, we can contribute to a better understanding of violent conflict incidence under drylands vulnerability and of the role of natural resources therein without denying the role of political factors. The latter would probably be responsible for the remaining unexplained variance in conflict occurrence.

Our paper is structured as follows: We provide the conceptual and methodological background for the typology of drylands vulnerability from Kok et al., (2015, 2010, section 2). With this non-linear research design we investigate what the eight spatially explicit clusters constituting the socio-ecological typology of global drylands vulnerability tells us about the distribution of conflicts therein (section 3.1). Then we ask in how far using this typology method compares to traditional linear methods of mono- and multivariate fits in terms of statistical explanatory power for this incidence or lack of conflicts (section 3.1).

We then qualitatively systematize the combinations of socio-ecological and environmental factors to explain these results by linking their cluster-specific interpretations to conflicts incidence or peace in the light of socio-ecological vulnerability (section 4). We ground truth selected interpretations with literature on conflict causes in the Horn of Africa (section 5).

We then discuss with what varying importance socio-ecological and environmental factors best determine conflict proneness and peace in drylands, taking the lack of political factors into the equation (section 6, discussion). By doing so we can conclude with what this contributes to explaining violent conflict, or peace, in the resource scarcity debate in view of a) a lack of generalizable statements in studies about the role of natural resource factors, and b) predominantly non-linear methodologies used for explanations (section 6, conclusions).

3.2 Methodology

3.2.1 Vulnerability Generating Mechanism in Drylands

Global drylands occupy 41% of the Earth's land surface and are home to half of the World's population living in poverty (Dobie 2001). These regions are characterized by low rainfall and high rates of evaporation. The marginal resources available in fragile environments to base livelihoods on are subject to a tight human-nature interdependence (Safriel et al. 2005), resulting in a high risk of overexploitation.

We investigated the spatial distribution of violent conflicts in drylands on the basis of the drylands vulnerability typology from Kok et al., (2015, 2010). They introduce a formalized method for identifying general mechanisms creating vulnerability in different places in the world and apply it to drylands. In the following two sections we summarize the vulnerability generating mechanisms in drylands and the steps for devising this typology.

Earlier studies have identified key mechanisms in drylands influencing the vulnerability of farmers (Geist et al. 2004; Jäger et al. 2007; Reynolds et al. 2007). In terms of the key components of these mechanisms, Reynolds et al., (2007) identify five key variables for the 'Dryland Development Paradigm', comprising high variability in rainfall, low soil fertility, sparse populations, isolation (e.g. remoteness from markets) and distant voice and remote governance. Key characteristics identified as constituting a typology of vulnerability specifically for drylands farmers, and threatening human well-being (hereafter HWB), include the increasing pressures on natural resources from a growing population, limited and insecure access to water and fertile soils, and soil degradation resulting from overuse, combined with the breakdown of traditional coping mechanisms, and barriers to alternative livelihoods (Geist et al. 2004; Kok et al. 2015; Safriel et al. 2005; Sietz et al. 2011; UNEP 2007)

Kok et al., (2015, 2010) and Sietz et al. (2011) revisited these mechanisms, focusing on the most prevalent ones observed in case studies in drylands literature. These include the overuse of scarce natural resources resulting in their degradation (Dregne 2002a), its negative feedback on agricultural production and income generation (e.g. Safriel and Adeel 2008), and the dependence of income generation on "soft and hard infrastructure" (e.g. Shiferaw et al. 2008) which also influences the improvement of agricultural techniques in conjunction with available capital (Thomas 2008; Twomlow et al. 1999). Sietz et al. (2011) provide thematic and spatial entry points to reducing vulnerability in such a typology of drylands vulnerability.

In order to quantitatively investigate drylands vulnerability, Kok et al. (2015) identified spatially explicit indicators with subnational resolution for the most important processes and elements of these mechanisms considering poverty, the conditions and use of natural resource, agro-constraints, population density and isolation (see also Sietz et al. 2011). Providing the basis for the typology in this study, Kok et al. (2015, 2010) used seven datasets at 0.5°x0.5° resolution as proxy datasets including (Table 3.1): the present state of HWB measured by gross domestic product per cap (hereafter income) and infant mortality rate (hereafter IMR); the state of the soil and water resource (hereafter natural resource endowment) measured by the annual renewable water availability and the soil resource measured by the agropotential; the potential overuse of these resources measured by the population density the present anthropogenic soil erosion rate; and the available infrastructure approximated by road density. The literature shows causal links of individual indicators to violent conflict. There are two major overlaps between our indicators for quantifying key mechanisms in drylands influencing vulnerability and indicators that are considered most robustly associated with civil war onset and internal armed conflict: Low income and large population consistently increase the risk of civil war across many studies (Hegre & Sambanis 2006). The negative relationship with GDP/cap is one of the most robust in conflict literature in general (Hegre & Sambanis 2006), and large population is one of the most robust links to the increased risk of internal armed conflict (e.g. Hegre & Sambanis 2006, Collier and Hoeffler 2004).

Subnational data on infant mortality rates based on 10,000 spatial units was supplied by CIESIN (2005), which we subsequently aggregated from 2.5x2.5 minutes to the spatial resolution of our study. CIESIN (2005) points out infant mortality as one key proxy measurement for poverty, which in turn Daw et al. (2011) broadly define as a lack of well-being. The GDP/cap data comprises national-level values. This exception is explained by the following arguments. GDP/cap on a national level was considered important to enable a differentiation between low-, middle, and high-income countries. Furthermore, there is a lack of feasible alternative subnational datasets. We decided not to use the potentially feasible subnational dataset of "gross cell product" per cap (Nordhaus 2006), because of multiple countries in drylands lacking data. This would have ruled out all of these missing cells for the overall analysis.

Finally, insights into its subnational differentiation of income distribution are allowed for by its joint analysis with the high resolution data on infant mortality (Waldmann 1992).

Table 3.1: Quantification of vulnerability creating mechanisms: Core dimensions addressed, main vulnerability dimensions, indicators identified and subnational proxy datasets to represent them.

Core dimension	Vulnerability dimension	Indicator	Proxy (Data source)
Human well-being	Income	Average per capita income	GDP per capita (UNSTAT 2005; The World Bank 2006)
	Distribution of income	Infant mortality	Infant mortality rate (CIESIN 2005b)
State of soil and water resource – natural resource endowment	Soil quality	Agropotential	Productivity of grassland compared to the maximum feasible (Bouwman, Kram, et al. 2006)
	Water supply	Renewable water resource	Surface runoff (Alcamo et al. 2000)
Overuse of natural resources	Demand for water	Population density	Population density (Klein Goldewijk et al. 2010)
	Soil overuse	Soil erosion (through water erosion)	Water erosion index (Hootsman et al. 2001)
Connectedness	Soft and hard infrastructure	Infrastructure density	Road density (Meijer et al. 2009)

3.2.2 Typology of Drylands Vulnerability

All data in global drylands was selected and admitted to the cluster analysis. The data mask for selecting drylands is based on the method for drylands characterization used by the CBD (Convention on Biological Diversity Programme, Sörensen 2007). The extent of the global drylands comprised 20,000 grid cells. It is based on an aridity coefficient defined as the ratio of annual precipitation and potential evapotranspiration.

Starting with the indicator data on drylands, Kok et al., (2015, 2010) looked for structures in the indicator datasets using a cluster analysis - employing the established partitioning method of K-means (Steinley 2006). The cluster analysis identified eight clearly distinguishable clusters (or "vulnerability profiles") with typical indicator value combinations describing specific conditions that create vulnerability for smallholder farmers. The eight clusters provide a global overview with subnational detail, thereby showing where they occur in different locations in drylands (see Figure 3.1). Importantly, this method keeps the indicators separate so that typical combinations of indicator values of environmental scarcities, overuse, and poverty-related factors can be interpreted, allowing us to relate them to conflict incidence. This contrasts aggregating these indicators to an index, e.g. for a one-dimensional method for ranking which would obscure an abundance of information. The spatial distribution and interpretation of each cluster establish the basis upon which the relation between conflicts and drylands vulnerability will be investigated.

Table 3.2 shows the characteristics and example locations of the clusters from Kok et al. (2015, 2010) according to the average value for each of the seven indicators. The clusters are categorized into four groups. One group comprises the two clusters occurring in high-income countries (hereafter HICs). The three other groups are located in low-and middle-income countries (hereafter LMICs) and refer to similar natural resource endowments (poor, moderate, and rich). Each group is constituted by two clusters that differ in human well-being and overuse. Examples of where the clusters are located are given to complement the map of their spatial distribution (Figure 3.1).

Table 3.2: Summary of drylands vulnerability cluster characteristics and distribution from Kok et al., (2015). The indicated colors are used to identify the clusters throughout this study. Grey shaded rows indicate clusters in high-income countries, white shaded rows indicate clusters in low- and middle-income countries.

Cluster (color)	Group characteristics	Main characteristics	Examples of locations
Developed, less marginal (purple)	Very high average income, very low infant mortality rate	Very high agropotential, moderate road density, very high soil erosion mainly caused by cropland irrigation	Arid areas of the HICs– mainly in the USA, Spain, Italy and Australia
Developed, marginal (light blue)		Low agropotential, very low population density and road density, low water availability, low soil erosion through livestock grazing	
Resource poor, moderate poverty (yellow)	Most resource-constrained and isolated areas of the world, very low renewable water resources and agro-potential, low soil degradation; very low water availability, very low population density and road density	Low average income, moderate IMR, moderate HWB	Transition zone between pastoral and sporadic, sparse forms of land-use in the desert fringes in America, Africa and Asia, driest deserts in the world (Atacama, Sahara, central Arabian Peninsula)
Resource poor, severe poverty (red)		Lowest HWB - very low average income, very high IMR, pastoral land use	Arid regions of Sub-Saharan Africa and Asia that are dominated by pastoral land-use
Moderate resources, more populated (dark blue)	Low water availability, medium to very high agropotential, low average income, high IMR, low population density and road density	Very high agropotential, moderate soil erosion	Parallel bands in steppes and savannahs and neighboring desert areas, with the pink cluster more commonly adjacent to the desert. This typically coincides with a land-use gradient from pastoral to agro-pastoral uses
Moderate resources, less populated (pink)		Moderate agropotential, high soil erosion	
Resource rich, overuse (green)	High natural resource endowment, high water availability	Very high overuse - very high soil erosion, high agropotential, low HWB; very high population density and road density	Indus River, Tigris-Euphrates river system, Volga River, other irrigated areas like the Aral Sea area, regions adjacent to the eastern Andes
Resource rich, rivers (black)		Moderate HWB (highest in developing country clusters), high disparities, moderate agro-constraints, very high water availability	Indus River, Tigris-Euphrates river system, Volga River, other irrigated areas like the Aral Sea area, regions adjacent to the eastern Andes

3.2.3 Violent Conflict Data

In order to investigate the relation between conflicts and drylands vulnerability a geo-referenced dataset of violent conflicts is required. We used the following criteria for selecting the conflict dataset: data indicates violent conflicts; conflicts are assigned to a pair of geographical coordinates as opposed to (administrative) units of spatial reporting; global coverage; database dates back to at least 1990. We chose 1990 as the starting point for systemic and data-related reasons. First, this time represents a marked change in the emergence, occurrence and systemic causes of many conflicts (Harbom et al. 2007). Second, the focus of our study is on the most recent state of affairs in a time frame for which data availability and quality is best. Finally, indicator data and ruling out retro-causality with conflicts before 1990 would become more prone to data gaps and less robust the further back in time the conflicts would go before 1990 due to the stronger reliance on hind-casted modeled data, and observed data with less coverage.

We chose the Armed Conflict Dataset from the Uppsala Conflict Data Program and International Peace Research Institute, Oslo (UCDP/PRIO ACD, version 4-2006, hereafter PRIO ACD) as the violent conflict database. It contains annual entries of armed conflict with at least 25 annual battle-related deaths from 1946-2005. PRIO ACD defines armed conflicts as '…a contested incompatibility that concerns government or territory or both where the use of armed force between two parties results in at least 25 battle-related deaths' (Gleditsch et al. 2002). This threshold has been noted to correspond well with violent conflict narratives in view of environmental marginalization (Buhaug 2010; Witsenburg et al. 2009). All entries from 1990 to 2005 were extracted, regardless of their current state of activeness or inactiveness. This means that other types of conflicts (e.g. social) that do not concern government, territory or both, or violent conflicts without any battle-related deaths are not included. Multiple conflict years of the same conflict and conflict location were aggregated to one entry, i.e. one conflict point. For example, the multiple entries of the conflict between Israel and the Palestinians, which was assigned one conflict location in the database, were aggregated to one entry for study period from 1990 to 2005.

The PRIO ACD includes one pair of geographic coordinates in decimal degrees (point data) for each conflict entry. According to Raleigh et al. (2006) the center point for one conflict entry defines the midpoint of all known battle locations plotted on a map and is assigned to the nearest 0.25 decimal degree based on visual judgment to make it compatible with the 0.5°x0.5° spatial resolution of the indicators. The PRIO ACD dataset refined in the above manner comprises 116 armed conflicts.

The conflicts and eight drylands clusters were imported into a Geographical Information System in order to assign each conflict to one cluster. Conflicts located on the border between two or more grid cells were assigned to the cluster with the largest adjacent number of cells to this conflict. If necessary, this was repeated for the cells surrounding the adjacent cells.

3.2.4 Comparison with Common Approaches: Country-based Cluster Index, Logistic Regression Model

In order to make the explanatory power of predicting conflicts in drylands with clusters comparable with the explanatory power of a commonly used multivariate linear regression approach we calculated a country-based cluster index for each country. The multivariate approach is directly based on the seven underlying indicators, i.e. without the cluster information. Based on the clusters constituting the typology, the country-based cluster index is not a new cluster in the typology but rather the result of making information in the clusters comparable to mono- or multivariate fits on a country by country basis.

The country based cluster index reflects which clusters cover a country and how many cluster grid cells are within the country. First, we characterize each cluster $\boldsymbol{i}$ by the number of conflicts within the whole cluster divided by the number of grid elements constituting this cluster, resulting in a cluster specific weight $\boldsymbol{g_i}$. Then these cluster specific values – multiplied by the number of the respective cluster pixels within the country $\boldsymbol{N_i^j}$ – are averaged for each country $\boldsymbol{j}$. This generates a country-specific conflict proneness $\boldsymbol{CI^j}$, reflecting the spatial occurrence and dangerousness of the clusters.

$$CI^j = \frac{\sum_{i=1}^{8} N_i^j \cdot g_i}{\sum_{i=1}^{8} N_i^j} \quad (1)$$

Country-based conflict proneness from the cluster approach and regression analyses are compared with different mono- and multivariate indicator combinations for explaining incidence or lack of conflicts in a country. We expand these comparisons by applying the Receiver Operating Characteristic (ROC, Swets et al. 1983) for selecting an optimum model.

Due to the binary response variable (conflict or no conflict in a country) we use the logistic regression model (logit, Hosmer and Lemeshow 2000) to predict the probability of occurrence of an event i.e. the conflict in a country by fitting the frequency data to a logistic curve. The quality of fit of the mono- and multivariate logit fits was checked with the Akaike Information Criterion (AIC, Akaike 1974) and the residual deviance (Venables et al. 2002). The former can be used as a model selection criterion. It consists of a goodness of fit term (Residual sum of squares, RSS, i.e. LogLik) and a penalty term (number of parameters). The latter is comparable with the RSS in linear regression.

3.3 Conflict Incidence in a Typology of Drylands Vulnerability

3.3.1 Conflict Distribution

By using the 116 geocoded armed conflicts as an overlay over the spatial distribution of the eight drylands vulnerability clusters we gained insights into the distribution of armed conflicts in drylands and non-drylands (Figure 3.1). Table 3.3 summarizes the statistics in terms of area, population, and conflict.

Conflicts are proportionally distributed between drylands (46 conflicts, 40%) and non-drylands (70 conflicts, 60%), with respect to land mass area (roughly 33% to 66%). Thus, drylands are as conflict prone as non-drylands. This hints at an insufficient mono-causal explanation of conflict occurrence through water scarcity – a main characteristic of drylands. In contrast, conflict distribution in drylands is heterogeneous and concentrated. By only taking drylands areas into account with a population density greater than 0.5/km^2 (thus excluding one drylands conflict in the resource poor, severely impoverished red cluster) 91% of drylands conflicts are concentrated in four clusters that cover 40% of the total drylands area (Table 3.3), amounting to 36% of the 116 aggregated conflicts worldwide between 1990 and 2005. These four clusters are neither the most populated ones nor do they have the highest population density, raising initial questions about some of the broader neo-Malthusian claims about population pressure leading to conflict in drylands.

All 46 drylands conflicts are located in LMICs, while the other four are conflict free (see Table 3.3 and Figure 3.1 – they can both serve as a lookup tables for the clusters names and associated colors throughout the study, while Table 3.2 characterizes the clusters). Two of the conflict free clusters ("HIC cluster, marginal", light blue and "HIC cluster, less marginal", purple) are in HICs, and two (resource poor, moderate poverty, yellow cluster and the resource rich river cluster, black) are in LMICs. Four conflicts are located in unclassified drylands where the cluster analysis does not cover the CBD drylands mask. Conflict incidence also differs in developing country clusters with different levels of HWB, natural resource endowments and degrees of overuse. 50% of all drylands conflicts fester in the two "poor water, better soils" clusters with moderate natural resource endowment alone (dark blue and pink), and the second resource rich cluster "overuse" (green) is also disproportionately prone to conflict (22%), despite occupying a mere 5% of all drylands areas. Only 2% of people living in drylands live in the most impoverished "resource poor, severe poverty" (red), yet it is severely hit by conflict (20%).

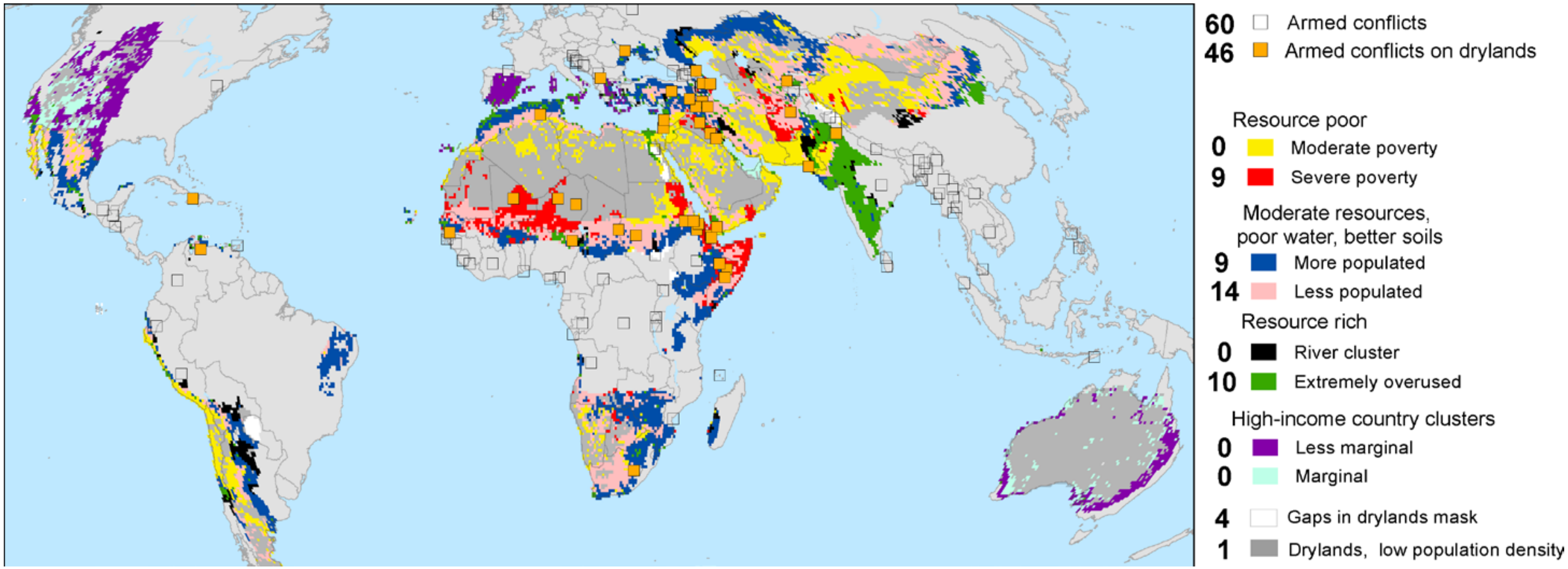

Figure 3.1: Spatial distribution of vulnerability of smallholder farmers and armed conflicts in drylands. Numbers indicate the conflicts within each cluster.

Table 3.3: General statistics of conflicts in drylands clusters, focusing on their portions with a population density greater than 0.5/km^2.

	Drylands				World
	Area (%)	Pop (%)	Conflicts (total)	Conflicts (%)	Conflicts (%)
Resource poor, moderate poverty	13	5	0	0	0
Resource poor, severe poverty	6	2	8	20	7
Moderate resources, more populated	14	11	10	20	9
Moderate resources, less populated	15	8	13	28	11
Resource rich, rivers	2	2	0	0	0
Resource rich, overuse	5	68	10	22	9
HIC, less marginal	5	3	0	0	0
HIC, marginal	3	1	0	0	0
Total	**62**	**99**	**41**	**89**	**36**
pop. dens. ≤ 0.5/km^2	36	<1	1	2	1
Gaps in cluster mask	2	1	4	9	3
Grand Total	**100**	**100**	**46**	**100**	**40**

A more formal problem needed to be addressed in this context with respect to retro-causality. Due to the fact that we are using the spatial distribution of typical value combinations of datasets from 2000 (and water availability from 2005, see Table 3.1) for explaining conflicts in the PRIO ACD database from 1990 to 2005, the question arises whether the conflicts are influencing the indicator values, vice versa, or both. For example, Witsenburg et al. (2009) indicate that negative consequences of conflict have wide spillover effects on many aspects of HWB in drylands. We addressed the question of retro-causality by comparing cluster results of the same indicators, but using data from 1990, to the results this study is based on (2000 and 2005). Comparing the results revealed the same number of clusters (eight), and highly stable vulnerability profiles and locations thereof, showing that the clusters and according vulnerability profiles already exist in the data from 1990. This result suggests that conflicts have not measurably influenced the indicator data. The sole reclassification of grid cells exceeding 1% of the overall drylands grid cells is from the “resource poor, severe poverty” (red) to “resource poor, moderate poverty” (yellow) cluster (2% of all drylands grid cells).

In conclusion, we find that armed conflicts are heterogeneously distributed across drylands with respect to the clusters, i.e. vulnerability profiles, ruling out population density and low precipitation as premature causes. While less impoverished profiles are less conflict prone, profiles with similar levels of poverty, overuse, population density, or natural resource scarcity show differences in conflict incidence. The next section discusses in how far these differences can be quantitatively explained with mono- and multivariate fits, and on the basis of the drylands typology.

3.3.2 Comparison with Mono- and Multivariate Fits

This section addresses whether the method establishing the drylands typology has measurable added value over directly using the underlying seven indicators in a logit-approach (Hosmer et al. 2000). We chose the country level as the spatial unit of investigation for this. In the case of the logit approaches the explaining variables are the country-wide averages of the indicators from Table 3.1. In the case of the using the indicators via the typology the explaining variable is the country-based cluster index as defined and described in section 2.4. The explained variable is the conflict occurrence in a country between 1990 and 2005. The conventional linear fits include monovariate regressions with all seven indicators, a bivariate fit using income and IMR to represent HWB, and a multivariate fit using all seven indicators, including natural resource conditions and their use. Finally, we compare these with the monovariate fit using the country-based cluster index.

As a first measure for the quality of fits we take the averaged deviance from the explained variable (residual deviance, solid line in Figure 3.2) which allows for comparing the quality of the different models. Within the monovariate approaches IMR yields the best explanation. Using this variable together with income slightly improves the result, while including the natural resource conditions and use improves the result considerably. We applied the AIC to exclude the possibility that this improvement is due to increasing the number of explaining variables to the 7-variable model, (dashed line in Figure 3.2). The AIC compensates for this effect by penalizing each result for the number of variables used. This rules out model improvement based, which needs to be controlled for in multivariate models. As the AIC improvement is also significant (although less impressive) we can conclude that in a multivariate logit framework the occurrence of conflicts is explained best by a combination of socio-economical and natural variables.

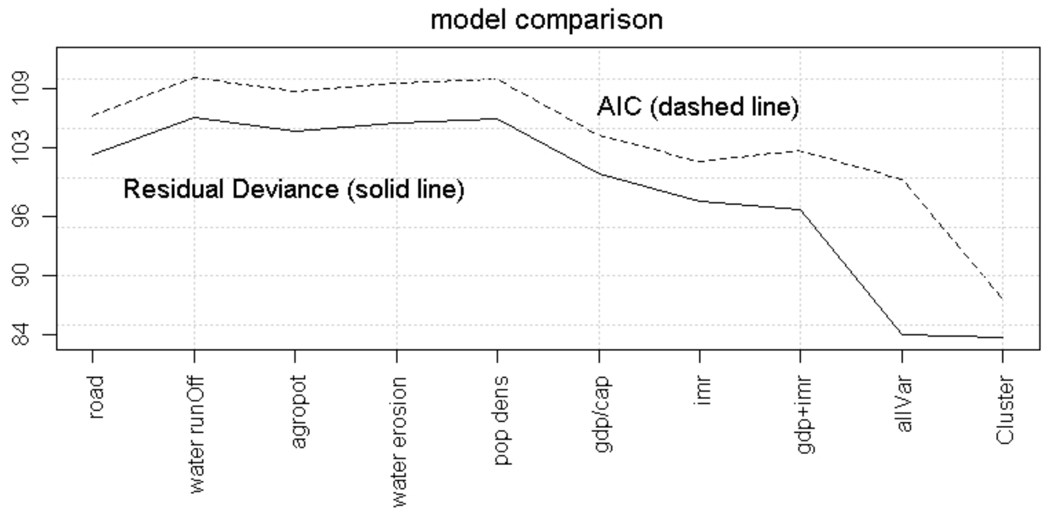

Figure 3.2: AIC and residual deviance for the models. AIC and residual deviance for comparing the models of the monovariate logit fit for each of the seven drylands indicators, the multivariate logit fits for income and IMR, all drylands indicators, and the country cluster index as the explanatory variable. Smaller values denote better fits. See Table 3.1 for full indicator names.

Now we compare the quality of the logit approach with the quality of cluster-based conflict explanation. The last column in Figure 3.2 shows that by using this variable in a monovariate logit approach both the residuals and the AIC are further reduced compared to the multivariate fit using all indicators (allVar). While the residual deviance only improves slightly, the AIC shows a large improvement due to the strong reduction of degrees of freedom. This means that the monovariate regression based on the non-linear clusters is the preferable model for the statistical explanation of conflict occurrence.

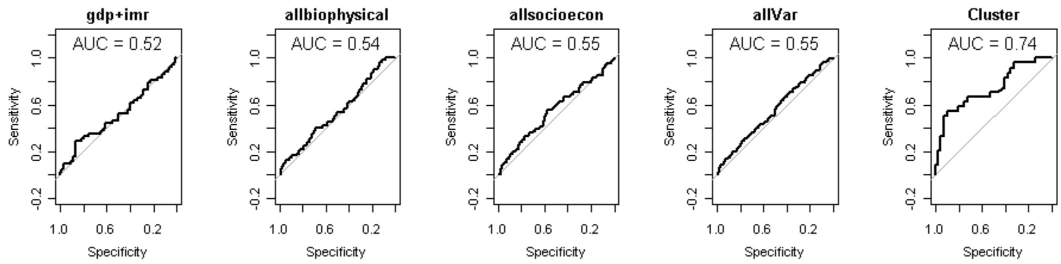

Figure 3.3: ROC for comparing the models of the multivariate logit fits for income and IMR, biophysical indicators, socio-economic indicators, all drylands indicators, and the country cluster index as the explanatory variable (from left to the right).

Evaluating the same set of models in a Receiver Operating Characteristic (ROC) also leads to the preference of the non-linear method (Figure 3.3). The ROC is a graphical plot showing the true positive rates (sensitivity) versus false positive rates (specificity) in predicting conflict incidence or absence with the country indices. The area under curve (AUC) indicates the accuracy of the test, or the ability of the model to correctly classify country indices with and without conflict (perfect classification being 1.00). Points on the diagonal line of no-discrimination (AUC=0.50) represent random guesses. Figure 3.3 shows how the models with income and IMR (AUC=0.52) and all variables (AUC=0.55) are largely random in terms of predicting a conflict incidence or absence. The model using the non-linear cluster information shows significantly higher predictive power (AUC=0.74) in discriminating between countries with and without conflict.

In conclusion, comparing these quantitative approaches for predicting violent conflict incidence suggest that the non-linear cluster approach is preferable over linear fits by showing measurable added value in both cases. This hints at the importance of dependencies between the explaining variables for explaining conflict incidence, which are not considered in multivariate linear regression and logit fits.

3.4 Linking Conflict Incidence to Cluster Interpretations

To additionally obtain a qualitative understanding of the relation between the vulnerability profiles and conflict occurrence, and of the dependencies between explaining variables, we now interpret the clusters as characterized by the seven normalized indicator values of each cluster's center, focusing on the dimensions of natural resource endowment, HWB, and overuse they constitute (Figure 3.4., left). The dimensions and indicators constituting them were introduced in section 2.1 and Table 3.1. Reflecting the structure in Figur 3.4., left, from top to bottom, the interpretations are subsequently grouped into differential analyses of LMIC clusters based on their low, moderate or high natural resource endowments in the following three subsections. Using the same grouping based on similar natural resource endowments, these sections provide the basis for the summarizing schematic diagrams (Figure 3.4., right) of how the typology of socio-ecological vulnerability in drylands relates to violent conflict distribution using a non-linear combination of these dimensions. These schematic diagrams are discussed in the subsection thereafter, concluding with whether the differential qualitative analysis of clusters provides explanations for the measurable added explanatory power shown in section 3.2.

The two conflict free clusters in HICs display significantly higher HWB than in the other clusters and are left out of the interpretation and schematic diagrams. This is justified by the different context in the higher income countries, requiring a different approach for analyzing conflicts (Markakis 1995).

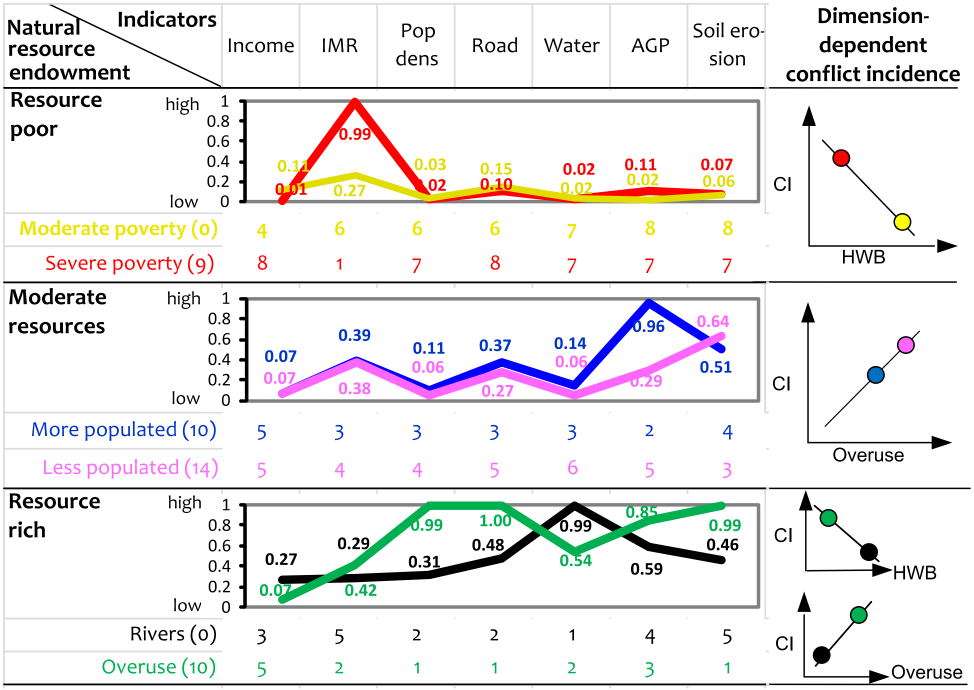

Figure 3.4: **Left:** Vulnerability profiles of the six clusters prevalent in LMICs grouped based on poor, moderate or rich natural resource endowment, ranks of indicator values across all eight clusters (1: highest), and number of conflicts in parentheses. The indicator values are min-max normalized between 0 and 1. The reading of the indicator ranges is from “low” (0), to “high” (1), as opposed to from “adverse” to “favorable”. Column header abbreviations for indicators: Income: Average per capita income; IMR: Infant mortality rate, Pop dens: Population density, Road: Infrastructure density; Water: Renewable water resource; AGP: Agropotential; Soil erosion: Soil erosion (through water erosion). **Right**: Schematic diagrams of conflict incidence as a function of the dimensions of natural resource endowment, HWB, and overuse. CI means conflict incidence; Human well-being (HWB) is a function of average per capita income and IMR; Overuse is a function of soil erosion and population density. For each group of similar natural resource endowment the circles with colors corresponding to the clusters colors show how the conflict incidence (y axis) relates to different degrees of HWB or overuse (x axis). The black diagonal lines show the direction of change in conflict proneness when changing the independent variables on, and the distances between circles approximate the differences.

3.4.1 Resource Poor Clusters Show Contrasting Conflict Proneness and HWB

The resource poor clusters show contrasting HWB (Figure 3.4, left, top). The yellow cluster (moderate poverty) has the second highest average income and the lowest IMR of any developing country cluster, and is the only cluster out of five with low HWB without conflict. At the same time it displays the most resource poor situation overall, resulting from natural conditions as opposed to overuse (lowest soil erosion). Its relative wealth is not based on agriculture. In consequence, livelihoods are predominantly based on other, less marginal resources and services, making conflicts over natural resources less likely than in the red cluster (severe poverty). Table 3.2 and Figure 3.1 provide insights into the locations of these clusters.

The comparably dramatic resource situation in the red cluster translates into the highest IMR and the lowest income by far, and into relatively high conflict incidence. Pastoral livelihoods in the poorest cluster covering arid regions of Sub-Saharan Africa and Asia are based on the scarcest water resources and extremely limited agropotential. Hence the resource situation resulting from natural conditions can be further exacerbated by extensive grazing or nomadic grazing and lead to desertification (Geist and Lambin 2004). This can threaten their livelihood basis and, according to the dryland livelihood paradigm, may subsequently lead to (further) poverty and violent conflict (Safriel and Adeel 2008). Furthermore, this cluster hosts the most sparse population density and lowest road density. Conflicts in the red cluster include conflicts between Ethiopia and the Afar Revolutionary Democratic Union Front (ARDUF), Niger and the Front for Democratic Renewal (FDR), and Mali and the Northern Mali Tuareg Alliance for Change (ATNMC).

3.4.2 Clusters with Moderate Resources and Low HWB Show Highest Conflict Incidence

24 out of 42 drylands conflicts (almost 60%) are located in the two clusters with moderate natural resource endowment and low HWB (Figure 3.4., left, middle). They show very high conflict incidence under high overuse (pink cluster, 14 conflicts), and less overuse and high incidence under high agropotential and slightly higher population density (dark blue cluster, 10 conflicts). They exhibit virtually identical values of low water resource availability/cap, low income, and moderate IMR.

The pink cluster shows the highest conflict incidence. Although its water stress is less severe than in the yellow cluster, the over-used soils and limited agropotential may not allow sound livelihood alternatives to secure a living standard under additional external pressures. Thereby it points to a particularly severe situation that limits people´s capacity to cope with any disturbances if they rely on the limited agricultural productivity for a living, while the much higher agropotential in the dark blue cluster offers alternatives. Both clusters show high conflict proneness despite HWB values similar to the conflict free yellow cluster, indicating that an explanation through poverty and resource scarcity alone is insufficient in their case.

Conflicts in the pink cluster include border conflicts between Eritrea and Ethiopia, Somalia and Ethiopia, conflicts in Lesotho and Botswana, and Uzbekistan and the Jihad Islamic Group (JIG). Conflicts in the dark blue cluster include conflicts between Macedonia and the National Liberation Army (UCK), Turkey and the Kurdistan's Worker Party, and Venezuela and the Military Faction under Hugo Chávez.

3.4.3 Resource Rich Clusters Show Contrasting Conflict Proneness and HWB

The highest water availabilities and 2nd and 3rd highest agropotential in the black ("rivers") and green ("overuse") clusters constitute the highest natural resource endowments. Similarly to the extremely resource poor counterpart, the pair shows contrasting income correlating with high or no conflict incidence (Figure 3.4., left, bottom).The conflict free black cluster is characterized by moderate agropotential, soil degradation and population density, and the highest water availability. This allows for moderate agricultural production enough for creating relative wealth. It is the only cluster with a moderate level of HWB in LMICs, with potentially conflict incidence reducing effects. On the other hand, this peace may be fragile as the high IMR points towards significant socio-economic disparities among the population. These disparities and related distributions of resources may induce future conflicts.

In the green "overuse" cluster the relatively good natural resource conditions are critically overstretched by a very high population density (68% of the drylands population, 5% of drylands area), inducing the highest soil degradation and highest pressure on resources. The second highest water availability and a high agropotential is translated into levels of HWB lower than in the moderately endowed clusters. In face of abundant yet overused resources people reliant on these resources to ensure their livelihoods are more likely come into conflict if the resources are depleted and no sound alternatives exist. Conflicts located in this cluster include conflicts between Israel and Palestinian factions, Lebanon and the Lebanese Army (Aoun), India and Sikh Insurgents, and Moldova and the Pridnestrovian Moldavian Republic.

3.4.4 Qualitative and Quantitative Support for a Non-linear and Multi-causal Explanation of Conflict Incidence

In conclusion, differential qualitative analysis of clusters classified through the dimensions of natural resource endowment (water resource availability and agropotential), HWB (average per capita income and IMR), and overuse (soil erosion and population density) offers explanations for why the non-linear models provide measurable added explanatory power. It does so by interpreting the number of conflicts in each cluster in the light of dependencies between these dimensions.

These results are synthesized in the following paragraphs and in the schematic diagrams in Figure 3.4, right using the same groupings of clusters based on low, moderate, and high natural resource endowments (from top to bottom). Pointing out tendencies, the two-dimensional diagrams in Figure 3.4, right, have a predominantly conceptual and qualitative character, rather than a quantitative one (see caption of Figure 3.4, right for details). The combination of indicators was principally motivated in section 2.1. and Table 3.1. They are combined to aggregated variables in the schematic diagrams (x axis) as follows: the lower IMR and higher income is, the better HWB is, and vice versa; the higher the soil erosion and population density are, the higher overuse is. As we are dealing with a discrete typology the changes are taken from the comparison of the two considered clusters.

In similar resource conditions conflicts occur when marginal and/or over-used natural resources coincide with more severe poverty (Figure 3.4, right, red cluster, green cluster). Less overused, or less marginal, resources are always less conflict prone (a-yellow, b-dark blue, c-black). HWB is the distinguishing dimension in extreme resource endowment cases (a, c), while overuse is in cases where natural resource endowment is sufficient for agricultural use beyond subsistence (b, c).

In this light, we conclude that resource scarcity is not a generally applicable explanation for conflict incidence in drylands. In the relatively resource rich environments income and population density-driven soil degradation differentiates between conflict proneness and its absence (Figure 3.4, c). Yet this finding is not applicable when comparing clusters with significantly different resource endowments (Figure 3.4, a-c). For example, conflict prone clusters with fewer resources have far lower population density than the conflict free “rivers” cluster. This indicates how the importance of HWB and overuse in explaining conflicts depends on a further dimension: The level of natural resource endowment appears to decide whether the HWB (through income and IMR) or overuse (through soil degradation) determines the conflict proneness.

With these findings the best explanation of conflict incidence through the cluster-based logit approach (Figure 3.2) and through the ROC (Figure 3.3) become understandable: As shown in Figure 3.4 the importance of the variables for the dimensions of HWB and overuse in explaining conflicts is different depending on the natural resource endowment. Such a relation can never be reproduced by a linear regression where the influence of a specific variable is necessarily independent from the values of the other variables.

From that we can understand why the vulnerability profiles from the cluster based approach explain armed conflict incidence in drylands better than linear regression approaches, and conclude that in the case of explaining conflict incidence with variables indicating vulnerability generating factors in drylands a non-linear approach allowing for such dependencies is the preferred method.

For what this means quantitatively for the relationship between these dimensions and conflict proneness we discern the ranges of indicator values that can always be associated with conflicts by taking the upper and lower quartiles (i.e. 50% of the grid cell values around the median value) of each indicator in each cluster into account. In the poverty dimension this applies to an IMR of 66 deaths per 1000 live births and higher (compared to an overall drylands range of values from 0.02 – 252.93 deaths), and a GDP/cap of USD 558 and less, (drylands range USD 122 – 34560); in the overuse dimension it applies to a population density of 126 people per km^2 and higher, or 0.5 and less (drylands range 0 - 300 people per km^2), and a water erosion index of 0.29 and higher (drylands range 0 - 0.58); in the natural resources dimension it applies to an agropotential of 0.005 to 0.015 KgC/m^2, and 0.254 KgC/m^2 and higher (drylands range of 0 - 0.55 KgC/m^2); runoff 6.5 to 326.4 $10^3m^3/(yr*km^2)$ (drylands range 0 - 500 $10^3m^3/(yr*km^2)$).

In addition, we compare the averages of the indicator values to discern what degrees of resource endowment, human well-being, and overuse are generally associated with either peace or conflict. With respect to the dimension of natural resource endowment, the lowest averages without conflict are a water runoff of 10.3 $10^3m^3/(yr*km^2)$ (yellow cluster), and an agropotential of 0.005 kgC/m^2 (i.e. kilograms of carbon when cultivating grassland, yellow cluster). Slightly less resource scarcity is associated with conflict in the red cluster. The highest averages that show conflicts are 229 $10^3m^3/(yr*km^2)$ for water runoff (green cluster) and 0.26 KgC/m^2 for agropotential (dark blue cluster). With respect to the dimension of poverty, the most severe averages without conflict are a GDP/cap of USD 2995 (yellow cluster), and 43 deaths per 1000 live births (black cluster). The least severe averages that still have conflicts are USD 2064 and 58 deaths per 1000 live births (both pink cluster). With respect to the dimension of overuse, the highest averages without conflict are a water erosion index of 0.177 (black cluster), and a population density of 79 people per km^2 (black cluster). The lowest averages that show conflicts are a water erosion index of 0.03 and 6 people per km^2 (both red cluster).

3.5 Ground Truthing - Exemplary Conflict Causes in the Horn of Africa and Vulnerability Profiles

This section investigates in how far general interpretations of conflict incidence with the vulnerability profiles in the light of the vulnerability generating mechanisms are viable for specific conflicts in the drylands sample. We relate the causes and locations of drylands conflicts in the Horn of Africa, i.e. in Ethiopia, Eritrea, Somalia, and Djibouti, to the pertinent profiles. The first three countries are among the 20 countries in the world with the lowest income (CIA 2012). “The Horn” has the highest conflict density in global drylands (8 out of 42 conflicts), and is a classic example for environmental degradation (Markakis 1995). Figure 3.1 shows that three vulnerability profiles are associated to this region (red, pink and dark blue). Human-environment systems reflected here include the predominantly subsistence-based pastoral use in lower lying areas under poor to severely poor human well-being, very low water availability, and low population density in the red and pink clusters (Eritrea, Djibouti, Somalia, and Danakil depression, Afar Region, Ogaden Province in Ethiopia), and agropastoral use in less water scarce, more mountainous regions with higher agropotential in the blue cluster (more mountainous regions in Ethiopia). Five conflicts are in the pink cluster, and two more are immediately adjacent to it.

In the following we investigate conflicts involving the Afar people and the states of Ethiopia and Djibouti in more detail, and discuss two that are directly related to the Ethiopian-Eritrean disputes (Raleigh et al. 2006). To different degrees, these conflicts are related to socio-economic, biophysical factors, and political factors.

3.5.1 Conflicts Involving the Afar – Red and Pink Clusters

The two conflicts in this area are between the Afar Revolutionary Democratic Union Front (ARDUF), and the Ethiopian government (red profile), and between the neighboring conflict between the Afar aligned FRUD (Front for the Restoration of Unity and Democracy) and the Djibouti government – backed Issa Tribe (pink profile). The Afar region on the northeastern Ethiopian frontier is a low-lying depression that exhibits high mean temperatures and very low annual precipitation sums. It is largely assigned to the red cluster showing the lowest natural resource endowment and severe poverty. The Afar people are one of the main pastoral groups in the Horn of Africa, and mobile pastoralism is the dominant type of land use (Rettberg 2010). Inter-clan conflict over scarce resources is a major conflict cause (Berhe et al. 2007) but nationalism (e.g. Afar against Issa in Ethiopia and Djibouti), and competition for power between political parties also play a role.

In the past, resources have been constrained for the Afar through droughts and floods (Rettberg 2010), and also through the Ethiopian government's installation of large centralized farms in the region where sufficient agropotential exists. This has cut off the Afar's resource base from important land and water resources (Getachew 2001; Markakis 2003; Rettberg 2010), contributing to the breakdown of long-standing and effective coping mechanisms, e.g. against natural resource scarcity and variability, and driven the pastoral communities into more severe poverty. How this fragile socio-ecological system exposed to environmental variability and non-inclusive government policies is empirically linked to conflict in the Afar region agrees well with our hypotheses of conflict caused within the red profile (Figure 3.4, top and text), where we argue that further restrictions of the resource base can subsequently threaten the livelihood base, and lead to violent conflict.

Similarly, the second conflict involving the Afar, and Djibouti – backed Issa Tribe, is over grazing lands they were forced off of and further compounds the problems outlined above (Rettberg 2010). It is located in the pink profile. We argued that despite more favorable HWB and natural resources than in the related red profile people´s capacity to cope with additional external pressures is limited due to their reliance on limited agricultural productivity, and a lack of livelihood alternatives (Figure 3.4, top and text). This can cause or prolong conflict, and deteriorate into the poorer and more resource-sparse red profile, which it is commonly adjacent to (e.g. in the low lying regions along the Ethiopian Border to Djibouti and Eritrea, and the Red Sea coast).

With respect to the causal relatedness with the indicators used for the cluster analysis, conflict relevant statements from case study literature (Getachew 2001; Markakis 2003; Berhe et al. 2007; Rettberg 2010) about conflict causes in the Afar Region are consistent with conflict interpretations through the profiles. While livelihood alternatives to secure a living standard are limited and can facilitate conflict under additional external pressures in the red and pink profile, this does not apply to the dark blue profile which is nearly conflict free in the Horn of Africa. Extremely high agropotential and less overuse make it less vulnerable to disturbances of the resources base which allows for agropastoral use beyond a subsistence basis. As a result, pastoral areas are more conflict prone than areas sufficient for agropastoral and alternative livelihoods, and a lack thereof in the red and pink profiles appears to pose enough adverse boundary conditions to foster conflict – acknowledging the room for further conflict causes.

3.6 Discussion

Our results show that systematic quantitative and qualitative relationships exist *between* environmental and socio-ecologic factors that explain the distribution and incidence of violent conflict in drylands without including political variables. Differential qualitative analysis of typical value combinations of these variables provided explanations for the measurable advantages of this non-linear approach over commonly used linear fits. Nevertheless, the modeling results in Figure 3.2 and Figure 3.3 show that there is room for improving of statistical explanatory power in follow-up studies. In this light we discuss three relevant aspects in the following– the availability of global subnational datasets, the incorporation of political factors and rigorous regional, high resolution validation.

Interpreting the distribution and incidence of violent conflict case studies in the Horn of Africa through the vulnerability profiles leads to plausible, consistent results. It also indicated a situation where additional indicators would be useful to describe further relevant local conflict causes, pointing out directions for follow-up studies - two conflicts from the drylands sample that are directly related to the Ethiopian-Eritrean border conflict between the Eritrean and Ethiopian government, and between the Ethiopian government and EPLF (Eritrean People's Liberation Front). Here (Lata 2003) showed that political factors are important.

One impediment for accounting for all the underlying local mechanisms driving conflict in a global study of vulnerability is the scarcity of relevant, spatially and temporally well-resolved socio-political data with subnational resolution (Blattmann and Miguel 2010, Sietz et al. 2011). With respect to the political dimension and feasible datasets to formalize it, such studies should focus on including data on political marginalization (Buhaug 2010), and governance issues (Getachew 2001). While the global availability of such data on these aspects is limited, this may further systematize conflicts in drylands by moving towards a "socio-ecological-political" typology to further reduce the unexplained variance. Exemplarily, incorporating an adequate indicator for political marginalization would likely reduce the unexplained variance in our model introduced in section 3.2. Detailed statements on how this might influence our results are more speculative, because compiling this indicator for global and spatially explicit subnational studies would be more challenging. The inverse world governance indicator of voice and accountability is a candidate. On a national basis it captures citizen's ability to participate in selecting their government, as well as freedoms of expression and association (Kaufmann et al. 2010), yet would mask subnational variations, group or community marginalization. Combining it with a geocoded subnational dataset on ethnic power relations (Wucherpfennig et al. 2011) for identifying all politically relevant ethnic groups and their access to state power may resolve this issue.

We account for critical socio-economic and environmental factors specific to drylands vulnerability. The typology, i.e. variable value combinations, offers systematic explanations for violent conflict incidences in drylands with a limited set of variables. If the political dimension were the sole dominating driver of violent conflict in drylands, the systematic behavior of socio-ecological variables would not be discernible. The debate on the role of natural resource factors in explaining violent conflict exemplarily shows is that factors for explaining violent conflicts, or conflict types, in separate studies are not always equally significant. In our point of view, this further suggests that promising for large-N studies to account for varying importance of explaining variables, and interdependencies between them, in their research design. For example, in a comprehensive statistical analysis of empirical results from numerous other studies linking factors to violent conflict onset, Hegre and Sambanis (2006) confirm the robustness of the relationship between two key variables of income (negative) and population (positive) with the risk of internal armed conflict, respectively. A third key variable, the length of peacetime until the conflict outbreak (negative relationship) is only robustly significant for a certain type of violent conflict.

In principle, the plethora of locally important factors that generate drylands vulnerability and also pose links to the incidence of conflicts such as the scarcity and management of natural resources (Sietz et al. 2012) can inevitably be reflected only to some extent when working at a global scale. Nevertheless, in dealing with the complexity of drylands, Sietz et al. (2011) have provided valuable insights into drylands vulnerability reduction at this scale. Their findings deduce thematic and spatial entry points for vulnerability reducing measures based on a typology of drylands vulnerability, and support the prioritization of strategies for improved drylands development. Insights gained at the global scale are suitable to stimulate local to regional investigations in order to further elaborate the knowledge established so far. Reflecting on the limitations of working at a global scale, typical mechanisms identified at the global scale were further specified in the contexts of the Peruvian Andes and Northeast Brazil (Sietz et al. 2012, Sietz 2013). These regionalizations indicate possible approaches to refining the insights gained in the conflict-oriented context of this study or comparable studies to further understand violent conflict in drylands.

3.7 Conclusions

This study applied results from a non-linear and spatially explicit methodology emanating from global and environmental change research for analyzing vulnerability on drylands to a peace research related problem. Motivated by an inconclusive debate over implications of resource scarcity for violent conflict, and prevalent reliance on national data and linear models for explaining conflict in the literature, the study addressed a lack of studies on the socio-ecological vulnerability-violent conflict nexus in global drylands on a subnational level. We conclude this study with the potential broader significance of its methodological and content-related findings for what drives peace and conflict in drylands, and by suggesting future research for expanding on similar approaches.

Following Reynolds et al. (2007), Safriel and Adeel (2008) proposed that "…much of the controversy over the biophysical and social dynamics of livelihoods in the drylands can be resolved by recognizing that these processes may be non-linear" (p.121). Acknowledging this, we argue that this may also be the case in the controversy over the role of resource scarcity in explaining violent conflict in drylands. This is what the findings of our study on armed conflict distribution suggest when analyzed through the lens of a typology of socio-ecological vulnerability. While large-N studies commonly rely on essentially linear research designs, we argue that non-linear research designs may allow a more nuanced view and argumentation when aiming for regional and global overviews, yet considering local specifics, as supported by O'Loughlin et al. (2012) and Hsiang et al. (2013). Importantly, while non-linearity is discussed in the debates, e.g. on the implications of climate change on violent conflict (e.g. Buhaug et al. 2008), it is not well represented in methodologies to investigate what drives violent conflict. This may explain why empirical and quantitative research focusing on general relationships between resource scarcity and violent conflict are the subject of much debate: variations of importance of factors across these regions, e.g. drylands, can be substantial (e.g. O'loughlin et al. 2012). The method applied in this study may contribute to disentangling these variations.

We found that conflict incidence is heterogeneously concentrated across global drylands according to typical profiles of socio-ecological vulnerability. Four profiles distributed across low- and middle-income countries comprised all drylands conflicts. We showed that conflict occurs in all degrees of natural resource endowments of these profiles. We found that conflict proneness non-linearly decreased with increasing human well-being. In similar endowments conflict generally increased with lower endowment and/or more overuse. In low and high endowments conflict was absent when less overuse converged with less human well-being, i.e. less poverty and higher income. Generally, the most adverse averages of poverty and income in systems without conflict were GDP/cap of USD 2995, and 43 deaths per 1000 live births. The highest averages of overuse without conflict are a water erosion index of 0.177, and a population density of 79 people per km^2. The lowest averages resource endowments without conflict are a water runoff of 10.3 $10^3 m^3/(yr*km^2)$, with an overall range in drylands from 0- 500 $10^3 m^3/(yr*km^2)$, and an agropotential of 0.005 KgC/m^2 (i.e. kilograms of carbon when cultivating grassland, drylands range from 0 - 0.55 KgC/m^2).

Conflict does not generally increase with resource scarcity or overuse. A systematic explanation of conflict incidence and absence across all different degrees of natural resource endowments is only reached through varying importance of human well-being and resource overuse depending on the level of endowment - a relationship that is irreproducible by commonly applied linear regression, or mono- or multi-variate logit models. This showed that the influence of these factors – in this case socio-economic and environmental - is dependent on their value combinations, and that a methodology that accounts for this leads to better understanding of violent conflict and its absence in drylands. If the political dimension were the sole dominating driver of violent conflict in drylands, the systematic behavior of socio-ecological variables would not be discernible. We expect including this dimension will further reduce the unexplained variance in the model in case appropriate subnational proxies covering global drylands are derived for future studies.

We concluded that resource scarcity is not a generally applicable explanation for conflict incidence in drylands. Conflict and peace are prevalent under similar scarcities of natural resources in socio-ecological systems. Closer inspection of their vulnerability profiles showed that under poverty both naturally scarce and better endowed yet overused natural resources drove violent conflict. On the other hand, very similar low income was observed in both conflict free and conflict ridden profiles. To our opinion this showed that two "extreme" positions of purely resource scarcity induced conflict ("neo-Malthusian" position, Homer-Dixon 1991) or purely economically/socially/politically induced conflict ("Durkheimian" position, Shaw and Creighton 1987) provide the most insight into the distribution and concentration of violent conflict incidence in drylands when they are combined, ruling out mono-causal and blanket statements.

Regional or global research using more localized data on conflict has commonly been proposed as a primary next research step in terms of quantitative studies of environmental change influencing violent conflict incidence (Buhaug 2010; Burke et al. 2009). Using increasingly improved and available geo-referenced and disaggregated conflict data sets for Africa, such as the Armed Conflict Location and Event Data (ACLED, Raleigh et al. 2010) and the Uppsala Conflict Data Program Geo-referenced Event Dataset (UCDP GED (Sundberg et al. 2011)), could corroborate the added values of this study by testing the outcomes in a more disaggregated approach and with data including recent conflicts from 2006-2011. This would allow for a more rigorous validation of our findings in line with newer validation studies (e.g. Fekete 2009; Krömker et al. 2008; D. Sietz et al. 2012) to further strengthen the credibility of our study. This would also provide a setting to test the method with different types and definitions of violent conflict by investigating how they relate to the socio-ecological typology of vulnerability.

Acknowledgements

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4 Global Typology of urban coastal vulnerability under rapid urbanization[3]

Abstract

Coastal areas are urbanizing at unprecedented rates, particularly in low- and middle-income countries. Combinations of long-standing and emerging problems in these urban areas generate vulnerability for human well-being and ecosystems alike. This baseline study provides a spatially explicit global systematization of these problems into typical urban vulnerability profiles for the year 2000 using largely sub-national data. Using 11 indicator datasets for urban expansion, urban population growth, marginalization of poor populations, government effectiveness, exposures and damages to climate-related extreme events, low-lying settlement, and wetlands prevalence, a cluster analysis reveals a global typology of seven clearly distinguishable clusters, or urban profiles of vulnerability. Each profile is characterized by a specific data value combination of indicators representing mechanisms that generate vulnerability. Using 21 studies for testing the plausibility, we identify seven key profile-based vulnerabilities for urban populations, which are relevant in the context of global urbanization, expansion, and climate change. We show which urban coasts are similar in this regard. Sensitivity and exposure to extreme climate-related events, and government effectiveness, are the most important factors for the huge asymmetries of vulnerability between profiles. Against the background of underlying global trends we propose entry points for profile-based vulnerability reduction. The study provides a baseline for further pattern analysis in the rapidly urbanizing coastal fringe as data availability increases. We propose to explore socio-ecologically similar coastal urban areas as a basis for sharing experience and vulnerability-reducing measures among them.

Keywords: Coastal cities, cluster analysis, vulnerability-generating mechanism, socio-ecological system, indicator-based analysis

4.1 Introduction

Urbanization is a defining phenomenon of our time (Hoornweg et al. 2011). Most urbanization takes place in the developing world, and cities are disproportionately located along rivers and coastlines (Grimm et al. 2008). 40% of the world's population inhabit a narrow coastal band that takes up 7% of the Earth's land area (McGranahan et al. 2007).

Urban life is radically changing coastal environments through unmanaged population increase (Grimm et al. 2008), urban expansion (Seto et al. 2011), and resource demand (Bloom 2011). Moreover, coastal cities are particularly at risk of flooding due to tropical storms and sea level rise (Handmer et al. 2012). Altogether, long-standing and emerging socio-economic and biophysical problems for coastal cities are compounding due to the magnitude and acceleration of transitions (Tanner et al. 2009). In rapidly growing cities in low- and middle-income countries (LICs and MICs) in particular, these problems risk to outpace the efforts to reduce vulnerability (O'Brien et al. 2012; UN-HABITAT 2011; UNISDR 2011): They increase exposures and sensitivities of urban populations and ecosystems (McGranahan et al. 2007), and overstretch municipal management and planning capacity (Grubler et al. 2012; Prasad et al. 2009).

Regional and local case study literature shows that there are different types of vulnerability in urban coastal areas, the challenges outlined above are unevenly distributed geographically, and that these challenges are further exacerbated by the speed of urbanization. For example, urban areas exposed to

[3] This article is currently in review by the ISI-listed Journal Plos One.

floods show significant variations in rates and magnitudes of urban expansion, which contribute to significant variations in exposure (Güneralp et al. 2015). Despite this knowledge about these challenges for cities in low- and middle income countries, and the vulnerability they generate for their populations, there is a lack of integrated studies on a regional or global scale that systematize the challenges for different types of cities at various locations. Garschagen & Romero-Lankao (2013) point out that greater scientific attention is needed for the linkages between different components of vulnerability of urban populations. This could identify entry points to enhance the adaptive capacity at the city and national level, strengthen resilience for coastal cities under rapid growth, and facilitate learning in city networks.

The recent emergence of international city networks on the subject of climate change hints to shared interest of cities in collaborating and learning from each other to improve their adaptive capacity under rapid urbanization. Besides local case study knowledge this requires generic insights that acknowledge local specifics and still constitute a global picture of coastal vulnerability of urban populations. While a general scaling up of effective vulnerability-reducing measures is difficult (Sietz et al. 2011), indicating which urban areas would be relevant for similar urban areas elsewhere would be an important step into that direction.

Some studies analyze socio-ecological problems based on recent or projected future biophysical risks in a limited number of coastal cities or urban areas. McGranahan et al. (2007) assess the geographic and climate change-related risks for urban settlement in the heavily populated low elevation coastal zone (LECZ). Hanson et al. (2011) and Hallegatte et al. (2013) quantify current and future economic impacts of climate change-induced sea level rise and flooding for 3o and 136 coastal cities, respectively. Tanner et al. (2009) assess climate change resilience in 10 rapidly urbanizing cities in predominantly coastal settings in developing countries. De Sherbinin et al. (2007) examine the vulnerability of three coastal megacities to current and future climate hazards using a vulnerability framework in which multiple reinforcing biophysical and socio-economic stresses are considered.

Some regional and global-level studies have also recently emerged, which focus on vulnerabilities in urban areas. Yet none focus on rapid growth and the coastal fringe per se. On a regional level, Muis et al. (2015) estimated the future change of flood risk under consideration of both climate change and urban expansion in Indonesia. In addition, they assessed the effectiveness of policy response options for vulnerability reduction. On an global level, Güneralp et al. (2015) estimated the future changes of urban exposure to floods and droughts in a detailed spatially explicit study, paying particular attention to the LECZ. Birkmann et al. (2016) used national and urban indicator data on hazards and socio-economic characteristics for generating an urban vulnerability index to natural hazards on a national level, showing that vulnerability was higher in moderate to fast-growing cities between 300,000 and 5mn inhabitants.

There is a need for identifying patterns among the diversity of cities from which conclusions can be drawn for transforming urban areas to sustainability (German Advisory Council on Global Change (WBGU) 2016). This paper aims to identify the first spatially explicit typology of vulnerability of urban populations under rapid urbanization along the global coastal fringe with subnational spatial resolution. For this area we present a first-order systematization of typical causes of urban socio-ecological vulnerability under rapid urbanization. Thereby annual urban population increase greater than 2.25% denotes above average, or rapid, urban population increase according to the UN World Urbanization Prospects, which is equivalent to at least 25% increase from 1990 to 2000 (UNDESA 2008; see Supplementary Material for further details).

We seek to answer the following research questions:

a) In how far do urban coasts share characteristic socio-ecological vulnerabilities to co-occurring socio-economic and biophysical problems under rapid urbanization?

b) How are the selected urban areas positioned to deal with and reduce these shared vulnerabilities?

For this purpose we applied a formalized method based on clustering (Kok et al. 2015; Janssen et al. 2012). This method has been successfully applied before to identify and interpret socio-ecological problems which similarly generate vulnerability in global drylands on regional and local scales (Sietz 2014; Sietz et al. 2012, 2011; Kok et al. 2010).

4.2 Methods and data

Our method for systematizing how and where vulnerability is typically generated follows a method of vulnerability analysis on an intermediate level of complexity and spatial scale proposed by Kok et al. (2015). The method consists of four steps:

1. Defining the relevant and distinct socio-ecological system for vulnerability analysis

We have defined rapidly urbanizing coastal areas as such a system in the introduction.

2. Identification of vulnerability creating mechanisms, core dimensions and indicators

Drawing from a multitude of case studies and meta-analyses of cases studies in the literature we list and briefly characterize well-documented mechanisms that have been found to typically generate vulnerability for urban populations in coastal urban areas. We identify core dimensions of these vulnerability-creating mechanisms. Then we identify indicator datasets that render quantitative information on, and can be interpreted in terms of the core dimensions.

3. Identification of vulnerability profiles and their spatial distribution

We submit these indicators to an established cluster analysis (Janssen et al. 2012; Lüdeke et al. 2014) to determine in how far typical indicator value combinations, which resemble vulnerability-creating mechanisms occur, and where they occur. Thereby each resulting cluster signifies an urban vulnerability profile.

4. Urban vulnerability profiles: characteristics, interpretation and verification

In this analytical step each urban vulnerability profile is characterized and interpreted. This is done in the light of the documented core dimensions of the vulnerability-creating mechanisms. Thereby we analyze what drives vulnerability in each profile, explain differences between profiles, and plausibilize these results with local realities according to case studies and meta-analyses of case studies. We employ each profile's spatial distribution, values for each indicator, and box plots to aid the analysis.

4.2.1 Identification of vulnerability-generating mechanisms, core dimensions, and indicators

Following a literature review we specified several mechanisms through which rapid coastal urbanization, i.e. rapid urban population increase, typically generates vulnerability**.**

Coastal cities are already disproportionately **exposed and sensitive to cyclones** (Hanson et al. 2011; Nicholls et al. 2007) **and floods** (Mondal et al. 2012; Hanson et al. 2011). Sections of most of the largest African coastal cities are currently at risk of flooding (IPCC 2012; Adelekan 2010; Awuor et al. 2008). Examples of cities that are subject to increasing exposure and sensitivity to climate extremes include Dhaka (storm surges, UN-HABITAT 2011) Sorsogon City, Philippines (Taifuns, Button et al. 2013), Mumbai, Rio de Janeiro, and Shanghai (Floods, De Sherbinin et al. 2007). The areas at risk are expected to significantly increase in the near term by **urban land expansion** (Güneralp et al. 2015) which is more rapid in low elevation coastal zones than in other places (Seto et al. 2011). It causes large-scale land cover change in LICs and MICs (Seto et al. 2012, 2011), i.e. in countries that are generally experiencing much higher levels of urban expansion and population growth (Angel et al. 2011). Unprecedented degradation and destruction of wetlands surrounding coastal urban agglomerations through increased demand for land (Baird 2009) and subsequent encroachment (Seto et al. 2012; McGranahan et al. 2007; Bravo de Guenni et al. 2005) destroys important ecosystem functions and services for the urban and surrounding populations, in particular flood regulation (Costanza et al. 2008; Bravo de Guenni et al. 2005; Hardoy et al. 2001). This was shown in New Orleans, after the landfall of Hurricane Katrina in 2005 (Törnqvist et al. 2008). Depending on the specific ecosystem functions the wetlands provide for the urban population their degradation has serious implications for urban livelihoods (Nicholls 2004).

Rapid urbanization is increasing the vulnerabilities in urban populations by overstretching **municipal management and planning capacity** (Grubler et al. 2012; Prasad et al. 2009; Tanner et al. 2009). The **rapid population growth** from in-migration and internal population increase can overwhelm basic urban services, especially if municipal adaptive capacity is initially low. This overstretch occurs when new problems arise before long-standing ones have been dealt with (Tanner et al. 2009). Future climate change, for example, is expected to further stretch the management capacity in coastal areas (Alam & Rabbani 2007, Dodman et al. 2011, De Sherbinin et al. 2007). Overstretched management has been well documented in case studies, e.g. in Dhaka, Dar es Salaam, (Dodman et al. 2011) and Mumbai (De Sherbinin et al. 2007). In the remainder of this article, the term ‚management' comprises both management and planning.

Rapid population increases are often absorbed into the urban fabric through an increase in densely populated informal settlements (Prasad et al. 2009). The growth in informal settlements is largely driven by poverty and **marginalisation of poor populations** in and around megacities in developing countries (Bravo de Guenni et al. 2005; Douglas et al. 2008) and is frequently underestimated (Kit et al. 2013). Informal settlements have less capacity to deal with shocks, e.g. climate-related extremes (Handmer et al. 2012; Huq et al. 2007; Hardoy et al. 2001) such as tropical cyclones and floods (Handmer et al. 2007), and less capacity to deal with the ensuing negative impacts (Bull-Kamanga 2003). This particularly applies when poor management, and low building and infrastructure quality coincide with densely populated areas (Prasad et al. 2009). Marginalization of the poor has been observed inter alia in numerous coastal cities in India (Revi 2008) and in Iliolo City in the Philippines (Rayos Co 2010). Under inadequate urban management and unchecked growth, informal settlements commonly encroach more risk-prone areas where flood and cyclone exposure is high (Cardona et al. 2012; Kit et al. 2011; Satterthwaite 2007). These areas are avoided by wealthier populations (Prasad et al. 2009). This leads to an increase in the number of vulnerable populations, population density, and low-quality buildings in floodplains. Informal settlement development in exposed areas has been observed in cities such as Lagos (Adelekan 2010), Mumbai (Chatterjee 2010), Esmeraldas, Ecuador (Luque et al. 2013), and many other large African coastal cities (Douglas et al. 2008).

Although future estimates of the additional number of people at risk from coastal flooding vary widely (Hinkel et al. 2014), all indicate a considerable increase due to surging populations in low-lying areas and to sea level rise. The ongoing superimposition of **sea level rise** on current flood levels increases the level of vulnerability in coastal cities to climate extremes (Frazier et al. 2010). This poses a major challenge for coastal management in terms of adapting to both rising storm surge levels and rising flood levels (UN-HABITAT 2011; Wilbanks et al. 2007). We summarize the major typical findings of the above-cited literature on urban socio-ecological vulnerability by identifying seven core dimensions and their interactions in Figure 4.1.

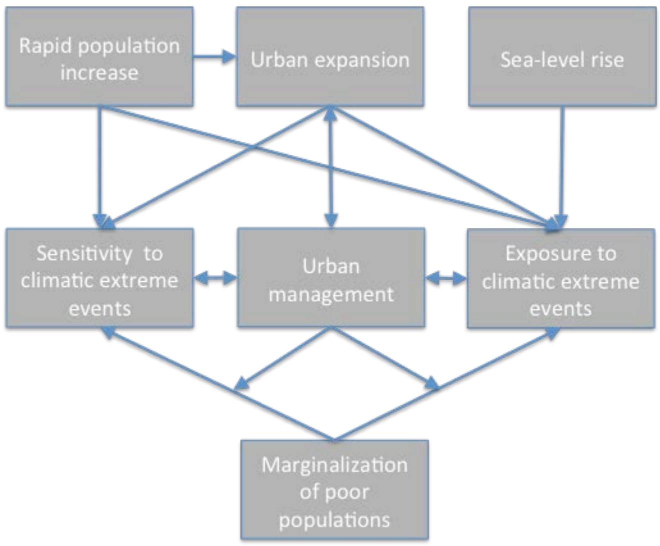

Figure 4.1: Core dimensions describing urban socio-ecological vulnerability under rapid coastal urbanization.

Rapid urban population increase typically increases the **exposure and sensitivity** of urban populations **to climatic extreme events** under overstretched or unwise **urban management**. The increase in exposure is also driven by unmanaged **urban expansion** into risk prone areas, and by **sea-level rise**. The increase in exposure and sensitivity is also driven by the **marginalization of poor populations** into risk prone low-lying areas and dense informal settlement development, and by degradation of flood regulating ecosystems such as wetlands through unchecked **urban expansion**, when **urban management** cannot effectively regulate development.

We identified 11 indicators with global coverage to render quantitative information on the core dimensions (Table 4.1). We did not impose a hypothesized predefined relationship between the indicators, following Kok et al. (2015). Instead, we (inductively) explored the structure in the data-space to obtain insights into typical vulnerability patterns. In Table 4.1 each indicator is attributed to one of the three vulnerability components commonly used in frameworks for vulnerability analysis in the context of global environmental change: exposure, sensitivity and adaptive capacity (Birkmann 2013; Patt et al. 2008; Schröter, Polsky, et al. 2005). Thereby we understand ‘damage’, e.g. from floods, as ‘exposure times sensitivity’.

Table 4.1: Indicators and datasets used, including their assignment to vulnerability components, the mechanisms they are related to, and the level of spatial data aggregation. The datasets predominantly have a subnational spatial resolution (0.5° x 0.5°, or 30 arc minutes). min.: minutes; sec.: seconds. The reasons for chosing each dataset, and details on data resolution and data treatment, are provided in the Supplementary Material.

Core Dimension	**Indicator**	**Vulnerability component**	**Dataset**	**Spatial resolution after aggregation**	**Original spatial resolution**
Rapid population increase	Rapid urban population increase	Exposure	Changes in urban population from 1990 to 2000 in percent of 1990 (Klein Goldewijk et al. 2010)	0.5°x0.5°	5 arc min.
Urban expansion	Urban expansion		Changes in urbanized area from 1990 to 2000 in percent of 1990 (Klein Goldewijk et al. 2010)	0.5°x0.5°	5 arc min.
Urban management	Government effectiveness	Adaptive capacity	Government effectiveness, aggregate and individual governance indicators (Kaufmann et al. 2010)	National	National
Marginalisationof poor populations	Average per capita income		Per capita GDP (UNSTAT 2005; The World Bank 2006)	National	National
	Slum population level	Sensitivity	Slum population in 2000 in percentage of the urban population (UN-HABITAT 2008)	National	National
Sensitivity to/ damage from climatic extreme events	Wetlands prevalence		Combination of prevalence of key wetlands, and the percentage of those that immediately surround urban areas (Lehner & Doell 2004; CIESIN 2005)	0.5°x0.5°	Polygon vectors (wetlands); 2.5 arc min.
	Cyclone damage	Damage	Fatalities per year from cyclones (Dilley et al. 2005), aggregated to 0.5° resolution	0.5°x0.5°	2.5 arc min.
	Flood damage		Fatalities per year from floods (Dilley et al. 2005), aggregated to 0.5° resolution	0.5°x0.5°	2.5 arc min.
Exposure to climatic extreme events	Cyclone occurrence	Exposure	Average relative frequency and distribution of cyclones (Dilley et al. 2005), aggregated to 0.5° resolution	0.5°x0.5°	2.5 arc min.
	Flood occurrence		Average relative frequency and distribution of high floods (Dilley et al. 2005), aggregated to 0.5° resolution	0.5°x0.5°	2.5 arc min.
Sea-level rise	Low-lying settlement		Total urban population currently living 2m or less above sea level; calculated using the digital elevation model SRTM v4.1 (Jarvis et al. 2008) and urban population data (Klein Goldewijk et al. 2010)	0.5°x0.5°	3 arc sec. (SRTM); 5 arc min.

A spatial resolution of 0.5°lon x 0.5°lat (30 arc minutes), which is compatible with the integrated assessment model IMAGE (Stehfest et al. 2014), was chosen for the indicators: The analysis presented in this paper focused on eliciting the most recent patterns of vulnerability based on a common time frame for all the data required. This is extensively discussed in the section “Discussion of the method”. However, there is a clear interest in how the patterns evolve over time, especially under future climate change. Integrated assessment models such as IMAGE can provide consistent data for future projections for this analysis, taking into account different assumptions and uncertainties. Using data projections from the IMAGE model Lüdeke et al. (2014) already analyzed projected changes in patterns of smallholder vulnerability to global environmental change in global drylands.

Many of the datasets used for the indicators were on a much finer scale, such as 3 arc seconds for Jarvis et al. (2008), 2.5 arc minutes for Dilley et al. (2005), and 5 arc minutes for Klein Goldewijk et al. (2010). These datasets were aggregated to 30 arc minutes for the analysis.

4.2.2 Identification of vulnerability profiles and their spatial distribution

We applied an established cluster analysis method to integrate the 11 datasets and to identify typical combinations in the data structure (Lüdeke et al. 2014; Janssen et al. 2012). The optimal number of clusters was identified by analyzing the stability of the results of allocating grid cells to clusters (see Supplementary Material for further details on the cluster analysis).

The Fraiman measure (Figure 4.5) was employed to investigate the importance of each indicator in shaping the clusters. With this measure we were able to determine how sensitive the cluster partition was to each single indicator by fixing it at its mean-value (so-called 'blinding' of indicators), and comparing 'blinded' runs of the clustering with the runs that included all indicators without blinding (Fraiman et al. 2008).

4.3 Results: Urban vulnerability profiles

Our analysis separates the rapidly urbanizing coastal fringe into seven robust and distinct vulnerability profiles. 84 out of a total of 196 countries (43%), and out of 153 countries with a coastline (55%), are experiencing rapid coastal urbanization. The geographical distribution of the seven profiles confirms that rapid urban growth is overwhelmingly a phenomenon in LICs and MICs (Figure 4.2). Table 4.2 summarizes key characteristics for vulnerability, examples of cities, geographical distribution, and population statistics in each of the profiles.

Closer inspection of differences in indicator values between profiles (Figure 4.3) reveals three groups of profiles. These groups separate significantly in regards to the rapid urban population increase indicator (see Figure 4.4) while the profiles within each group are characterized by similar values for most of their indicators. Group I shows the most rapid population increase (2 profiles), group II a rapid increase (3 profiles), and group III a less rapid increase (2 profiles). The two profiles within group I are significantly distinguished by cyclone occurrence and damage, and less so by flood occurrence and damage. Profiles within group II are significantly distinguished by wetland prevalence, and specific combinations of cyclone damage and occurrence. Flood damage is the distinguishing indicator in group III. The chosen grouping minimizes the mean absolute indicator difference between the profiles within each group compared to the inter-group differences. Furthermore four of the five indicators for intra-group distinctions are the most influential indicators for cluster identification (Figure 4.5, low Fraiman index).

In the subsequent sections the seven profiles are characterized using their specific indicator value combinations (Figure 4.3) and the core dimensions and the indicators relate to (Table 4.1). Each profile is named after a particularly representative city located in it to aid the reader. Each characteristic city is a particularly close match to its profile's average indicator values. (Each one is located in one of the 20 grid cells with the smallest Euclidean distance to the corresponding cluster center). The 21 studies used for plausibilizing the profiles are listed in the Supplementary Material (Table 3).

- "Maumere" profile – Most rapid urbanization and most severe poverty under lowest adaptive capacity
- "Sittwe" profile – Multiple severe biophysical and socio-economic problems under widespread poverty
- "Brus Laguna" profile - High flood damages from rapid urban expansion and reduced natural protection
- "Cebu" profile – Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement
- "Bluefields" profile – High damages and moderate occurrence of climate extremes: most severe climate change vulnerability
- "Agadir" profile – No severe problems under less rapid population increase and highest adaptive capacity
- "Muisne" profile - Extreme flood sensitivity under relative wealth and least rapid population increase

Figure 4.2: Spatial distribution of the seven urban vulnerability profiles under rapid coastal urbanization, and examples of cities located in these profiles. See Table 4.2 for a short description of the respective profiles.

Table 4.2: Vulnerability profiles - Key characteristics, city examples, and geographic distribution.

Profile group and profile	Key vulnerability characteristics	Examples of countries and geographical regions	Examples of cities located in profile	No. of coun-tries	% of global urban pop.	Urban pop. (m)	% of typology (No. of grid cells)
I: Fastest population increase and pronounced poverty under overstretched management							
I.1 "Maumere" profile	Most rapid urbanization and most severe poverty under lowest adaptive capacity	Most prevalent in Least Developed Countries, Sub-Saharan Western African and equatorial coasts; Yemen, Eritrea, Pakistan, Myanmar, Eastern Indonesia, Solomon Islands, Vanuatu; non-existent in Latin America	Maumere (Indonesia), Rangoon, Krong Koh Kong, Balikpapan, Monrovia, Conakry, Lomé, Libreville, Swakopmund, Massawa	41	1.8	51.4	18 (366)
I.2 "Sittwe" profile	Multiple severe biophysical and socio-economic problems under widespread poverty	Most prevalent in cyclone-prone Madagascar and Mozambique; Myanmar, Central Philippines, Belize; absent in South America	Small and middle-sized cities such as Sittwe (Myanmar), Toamasina, Mahajanga, Quelimane, Angoche, Sittwe, Tacloban, Labasa, Belize City	16	0.5	14.9	6.9 (140)
II: Rapid population increase and most rapid expansion intensify high flood damages under moderate adaptive capacity							
II.1 "Brus Laguna" profile	High flood damages from rapid urban expansion and reduced natural protection	Southern Brazil, Ecuador, Peru, Columbia, Venezuela, Algeria, South Africa, Lebanon, NW India, SE India, Mekong Delta, Java, Sumatra, Southern Malaysia	Brus Laguna (Honduras), Rio de Janeiro, Sao Paolo, Maracaibo, Caracas, lgiers, Istanbul, Oran, Durban, Accra, Luanda, Beirut, Ho Chi Minh City, Jakarta, Kuala Lumpur	39	7.3	209.6	21 (427)
II.2 "Cebu" profile	Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement	Subtropical coasts affected by tropical cyclones in Asia and Central America, majority of The Philippines, China, Vietnam, and Bangladesh; India (Bay of Bengal); nonexistent in Africa, virtually nonexistent in the southern hemisphere	Cebu (Philippines), Manila, Guangzhou, Shanghai, Fuzhou, Chittagong, Da Nang, Kolkata, Santo Domingo, San Juan, Puerto Cabezas	12	5.2	149.1	11.6 (237)
II.3 "Bluefields" profile	High damages and moderate occurrence of climate extremes: most severe climate change vulnerability	Subtropical coasts under less exposure to tropical cyclones in Asia (Southern Philippines, Indian - Bay of Bengal) and Central America (Belize, Guatemala, Honduras), The Caribbean (Southern Haiti and the Dominican Republic)	Bluefields (Nicaragua), Dhaka and Khulna, Chennai, Karachi, Maputo, Bhubaneshwar, Haiphong, Jacmel, Santa Marta (Columbia)	23	2.7	78.3	10.6 (215)
III: Few and less severe problems under slower population increase and high adaptive capacity							
III.1 "Agadir" profile	No severe problems under less rapid population increase and highest adaptive capacity	High-income countries on the Arabian Peninsula, Morocco, Tunisia, Guyana, Central Brazil, Turkey, Israel, Brunei, Malaysia	Agadir (Morocco), Abu Dhabi, Dubai, Doha, Muscat, Tel-Aviv, Bandar Seri Begawan (Brunei)	23	1	30.1	11 (223)
III.2 "Muisne" profile	Extreme flood sensitivity under relative wealth and least rapid population increase	Prevalent in South America, (e.g. Panamá, El Salvador, and NE Brazil) Magreb countries (e.g. Morocco, and Tunisia); Turkey, South Africa, West-Indian coast	Muisne (Ecuador), Esmeraldas, Natal, Fortaleza, Belém, Rabat, Tunis, Cape Town, Izmir, Antalya, Mumbai, Surat	43	3.6	102.9	21 (428)
SUM					26.6	209.6	2036

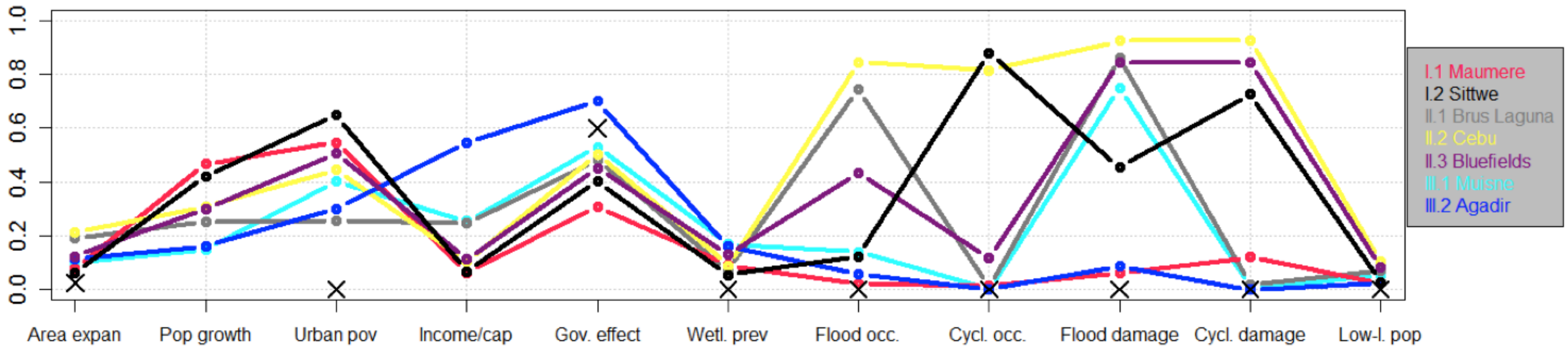

Figure 4.3: Vulnerability profiles and their average indicator values. The colored dots show the indicator values of the respective cluster centers. ‘X’ shows where the value is zero for each indicator. The indicator values are normalized between 0 and 1 using the minimum and maximum values for the different indicators. The colors are identical to those used in Figure 4.6 to depict the geographical distributions of the profiles. Each profile is given a name of a characteristic city located in it to aid the reader.

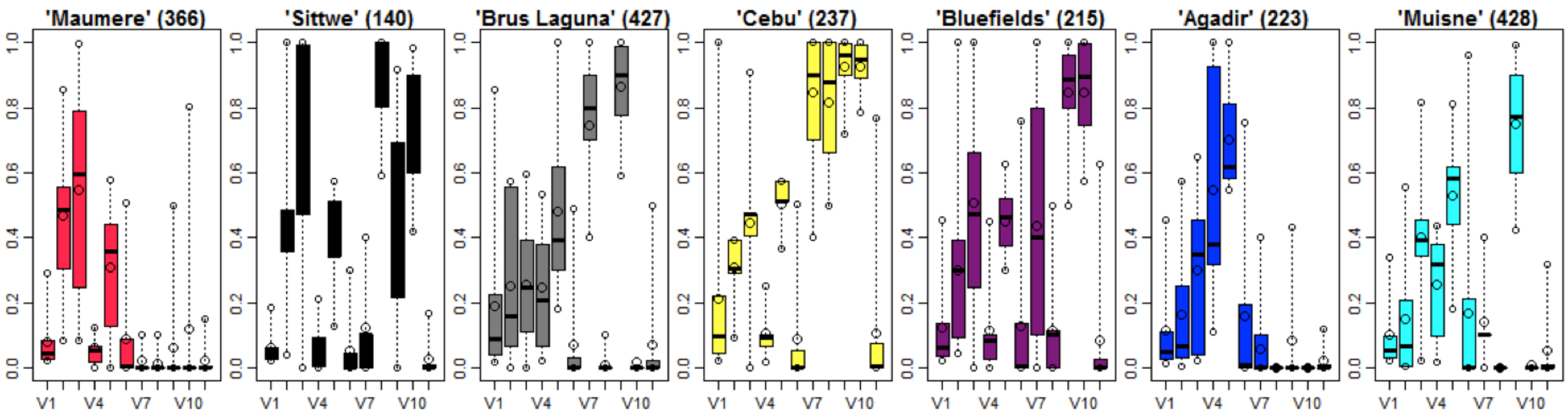

Figure 4.4: Box plots of the vulnerability profiles. They show the variation in indicator values (all indicator values are between 0 and 1) in each profile. The order of the indicators is identical to Figure 4.3. The boxes present the 25-75 percentile range of the indicator values; the circles at the end of the dotted lines indicate the 5- and 95-percentile, while the larger circle between them indicates the arithmetic mean; the black band in the box indicates the median value. The number of grid cells in a profile is indicated at the top of each frame.

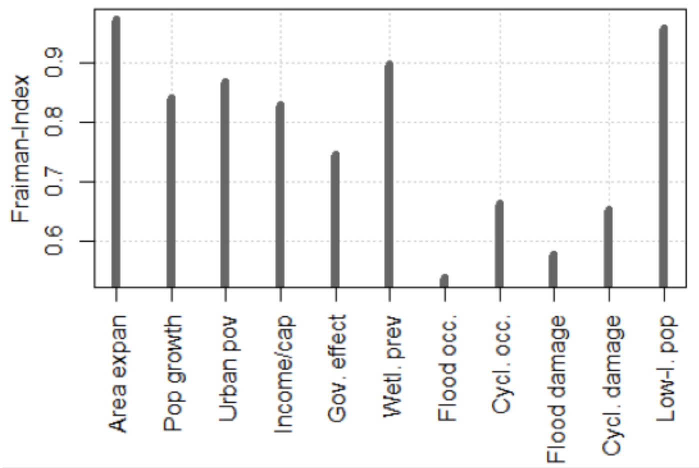

Figure 4.5: The Fraiman measure for each indicator. The values are between 0 and 1 and express the relative importance of each indicator in separating the clusters. The smaller the value, the more important the indicator is. The value shows the percentage of grid cells identically assigned when the corresponding indicator is blinded.

4.3.1 Group I: Fastest population increase and pronounced poverty under overstretched management

The red and black profiles in Figure 4.3 are characterized by extreme (i.e. severe) manifestations of problems: the most rapidly increasing coastal populations go together with the highest slum population levels of all profiles (i.e. the highest averages for these two indicators). The co-occurrence of the lowest increase rates in urban expansion hint at relatively dense informal settlement development. Judging by the lowest values for indicators of adaptive capacity - government effectiveness and income – urban management in this group is severely overstretched by such rapid growth and urban poverty. This indicates that the urban areas characterized by these profiles are in an extremely challenging position to reduce vulnerability. The two profiles significantly differ in cyclone occurrence and – less significantly - in damages from climate extremes.

Profile I.1: "Maumere" profile (red) – Most rapid urbanization and most severe poverty under lowest adaptive capacity

The red profile is named after the city of Maumere on Flores, Indonesia. Occurrence of and damages from climate extremes are characteristically low (no robust statements on recent sensitivity towards climate extremes are possible). They show the smallest indicator values and spread in the box plot, signifying a clear difference to profile I.2 (Figure 4.4). The Maumere profile is spatially restricted to Least Developed Countries (LDCs). For these countries the combination of high slum population levels, the most rapid urbanization and overstretched urban management is in line with general findings by Garschagen and Romero-Lankao (2013) and Cohen (2006) on the national level.

Profile I.2: "Sittwe" profile (black) – Multiple severe biophysical and socio-economic problems under widespread poverty

The relatively rare black profile is named after the city of Sittwe in Myanmar. In contrast to the Maumere profile these urban areas suffer from higher flood and cyclone damages. In fact, the African cities in this profile (Table 4.2) are considered the most at risk to cyclones in all of Africa (Brecht et al. 2013). These damages exacerbate the severe socio-economic problem structure of very high urban poverty, slum levels, and management overstretch, which is specific to group I. Exactly this combination of vulnerability-generating mechanisms is illustrated in the case study of Sorsogon City (Button et al. 2013).

Compared to the Maumere profile, relating the larger damages from floods with the low flood occurrence yields relatively high flood sensitivity. This can be explained by the lowest urban expansion rate of any profile, which indicates an absorption of burgeoning population increase through marginalization of the poor in dense informal settlements. This worsens existing risks for poor households which is a well-developed argument in developing countries (McCarney et al. 2011; Tanner et al. 2009).

4.3.2 Group II: Rapid population increase and most rapid expansion intensify high flood damages under moderate adaptive capacity

The three group II profiles (grey, yellow, purple) display the highest flood occurrences and damages, the highest totals of low-lying settlement, the fastest urban expansion rates, and relatively high wetland prevalence. In mechanistic terms, this indicates common urban expansion into flood-prone low-lying areas. The product of expansion rate and wetland prevalence is similar for the three profiles, indicating a high group-typical endangerment of the remaining natural flood protection. The three profiles subsumed under group II differ significantly in cyclone occurrence and damages, and differ to some extent in slum population levels and income.

Profile II.1.: "Brus Laguna" profile (grey) - High flood damages from rapid urban expansion and reduced natural protection

The grey profile is named after the city of Brus Laguna in Honduras on the Gulf of Mexico. It is a particularly distinct, robust structure in the data space, as it is discernable in clusterings with predetermined numbers of cluster from two to six as well. There is essentially no tropical cyclone activity (lowest occurrence and damages of all profiles). The lowest slum population levels and highest income in group II indicate high adaptive capacity to flooding, and low socio-economic disparities, for this group. However, in mechanistic terms, high flood occurrence, fast-paced urban expansion, reduced natural flood protection, and relatively high totals of low-lying settlement translate into high flood damages. This combination has been observed in a case study in Rio de Janeiro (which belongs to this profile) on vulnerability to current climate hazards (De Sherbinin et al. 2007).

The socio-economic situation in cities such as Rio, Durban, or Kuala Lumpur is clearly more favorable than in the related Cebu and Bluefields profiles.

Profile II.2: "Cebu" profile (yellow) – Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement

The yellow profile is named after the city of Cebu in The Philippines. The narrow indicator value distributions in the box plot signify a particularly distinct profile in the data space. In addition to the typical flood problems of group II, the very high occurrence of and damages from cyclones distinguish the Cebu profile. It is characterized by a severe confluence of problems: In mechanistic terms, the fastest urban expansion is taking place under highest overall damages from climate extremes and highest totals of low-lying settlement. A low prevalence of wetlands suggests that rapid urban expansion may be endangering the few existing natural flood-regulating ecosystems.

In regards to adaptive capacity, the high level of government effectiveness is comparable to profiles with much higher average income, less poverty, and lower occurrence of climate extremes. On the other hand, moderate slum population levels, and average income, indicate relatively low capacity to reduce the very high flooding and cyclone damages. Taking city case studies located in this profile into account, the relatively high marginalization of the poor, low income, and rapid growth suggest that the low-lying settlement areas are also inhabited by marginalized informal settlements: In Manila, for example, informal settlements at risk to coastal flooding make up 35% of the population (UN-HABITAT 2007). This combination of problems is also documented in Shanghai (De Sherbinin et al. 2007). A global ranking of population numbers in large port cities which are exposed to current coastal flooding (Hanson et al. 2011; Nicholls et al. 2007) shows that three of the four highest ranked cities are located in this profile (Shanghai, Guangzhou, and Kolkata).

Present flood damages in the Cebu profile show a high vulnerability to sea level rise due to its superimposition on coastal floods and storm surge levels. Hanson et al. (2011) and Nicholls et al. (2007) find that other cities in this profile, i.e. Shanghai, Guangzhou, Kolkata, Chittagong, and Ningbo, will be among the cities most exposed to coastal flooding in the 2070s due to sea level rise and storm surge.

Profile II.3: "Bluefields" profile (purple) – High damages and moderate occurrence of climate extremes: most severe climate change vulnerability

The Bluefields profile is named after the city of Bluefields in Nicaragua, and is prevalent in subtropical coasts with cyclone exposure in Asia, Central America, and The Caribbean. Differential analysis of the Bluefields and the Cebu profile reveals the most important distinguishing feature of this profile: Despite the lower occurrence of floods and cyclones damages from climate extremes are similarly high, resulting in the highest sensitivities in group II. The higher adaptive capacity (Bruce Laguna & Cebu) and less climate extremes (Cebu-profile not hit by cyclones) might explain this difference.

The evidently overstretched management in this profile is illustrated by a case study in Chennai: Uncontrolled urban expansion as well as blockage and encroachment of natural drainage systems have increased coastal and riverine flooding. The flooding overwhelms a lacking flood control response and the drainage systems (A. K. Gupta et al. 2010). Under these circumstances, relatively high wetlands prevalence alone does not significantly reduce high flood and cyclone-related sensitivity. The profile's extreme sensitivity to floods and storm surges has also been observed in Dhaka (UN-HABITAT 2011) and Maputo (Douglas et al. 2008): Even moderate flooding events have largely affected the urban poor.

In conclusion, the urban areas in the Bluefields profile appear to be in the weakest position to deal with climate extremes and future sea level rise.

4.3.3 Group III: Few and less severe problems under slower population increase and high adaptive capacity

Group III profiles are characterized by the highest average income and government effectiveness, relatively low marginalization, and low occurrence climate extremes. In mechanistic terms, the dark and light blue profiles are under the least pressure, and most favorably positioned to further reduce the few discernible problems: Urban management does not appear to be overstretched, and is subject to handling the "slowest" population increase rates. The two profiles subsumed under group III differ significantly in flood sensitivity, and less significantly in adaptive capacity.

Profile III.1: "Agadir" profile (dark blue) – No severe problems under less rapid population increase and highest adaptive capacity

The dark blue profile is named after the city of Agadir in Morocco, and is prevalent in MICs and high-income countries (HICs). Most effective government and highest income indicate a significantly better adaptive capacity than in any other profile. At the same time, cyclone and flood occurrence and damages alike are amongst the lowest in the entire fast-growing coastal fringe, leading to the lowest overall vulnerability to climate-related extremes. Therefore this profile starkly contrasts the fast-growing and managerially overstretched profiles in LICs.

In mechanistic terms flood occurrence can increase in the future through a combination of continued rapid urban expansion into wetlands (and other low-lying areas), and sea level rise. This combination of vulnerability-generating mechanisms has been suggested as a threat to unplanned rapid urbanization in coastal cities on the Arabian Peninsula (El-Raey 2009). In addition, the advantageous conditions to adapt to increasing flood exposure may lead to ignoring climate change adaptation requirements. This lack of precaution has been documented in the analysis of urban planning regulations in the Arab region (Tolba et al. 2009).

Profile III.2: "Muisne" profile (light blue) - Extreme flood sensitivity under relative wealth and least rapid population increase

The light blue profile is named after the city of Muisne in Ecuador, and is prevalent in MICs. In mechanistic terms, all vulnerability-generating problems are linked to high flood sensitivity. What distinguishes this profile from the wealthier Agadir profile and other profiles is the high flood damages under low flood occurrence in spite of relatively high average income and government effectiveness. The profile-based explanations for such flood sensitivity are a) marginalization of the poor in flood-prone areas under conditions of great socio-economic disparities, and b) a high differential impact of floods. This has been documented in Esmeraldas, Ecuador (Luque et al. 2013), as well as in cities such as Cape Town and Mumbai (cities with pronounced social disparities), where informal low-lying settlements lack drainage infrastructure (Mukheibir et al. 2007; Revi et al. 2014; De Sherbinin et al. 2007). Under these circumstances the high wetlands prevalence alone is insufficient for reducing major flood sensitivity.

4.4 Discussion

By interpreting urban vulnerability profiles in the light of the documented core dimensions, and plausibilizing the profiles using local case studies, typical and particularly problematic interplays of core vulnerability dimensions become evident. This discussion focuses on these interplays: six key vulnerabilities for urban populations, which have particular relevance in the context of urbanization, expansion, and climate change.

Rapid urbanization can also offer opportunities for reducing vulnerability (Birkmann et al. 2010; Garschagen et al. 2013), and can play an important role in economic development (Tacoli et al. 2008). Therefore, we also exemplarily explore profile-specific entry points for reducing these typical vulnerabilities.

4.4.1 Severely overstretched urban management (Group I and Bluefields profiles)

Global change vulnerabilities can outpace vulnerability reduction in rapidly growing LICs and MICs (UNISDR 2011; O’Brien et al. 2012). If overstretched management – indicated by ineffective government under low average income under a multitude of severe problems - is a proxy of this risk, then our study suggests that vulnerability reduction is being, or risks being, outpaced in over 50 (60%) out of 84 countries exhibiting rapid coastal urbanization (Figure 4.6, 1.). The three profiles that show the clearest signs of management overstretch (Sittwe, Maumere, and Bluefields profiles) account for over a third (36%) of all rapidly urbanizing coasts, and 145mn people (5% of the global urban population) in 57 countries.

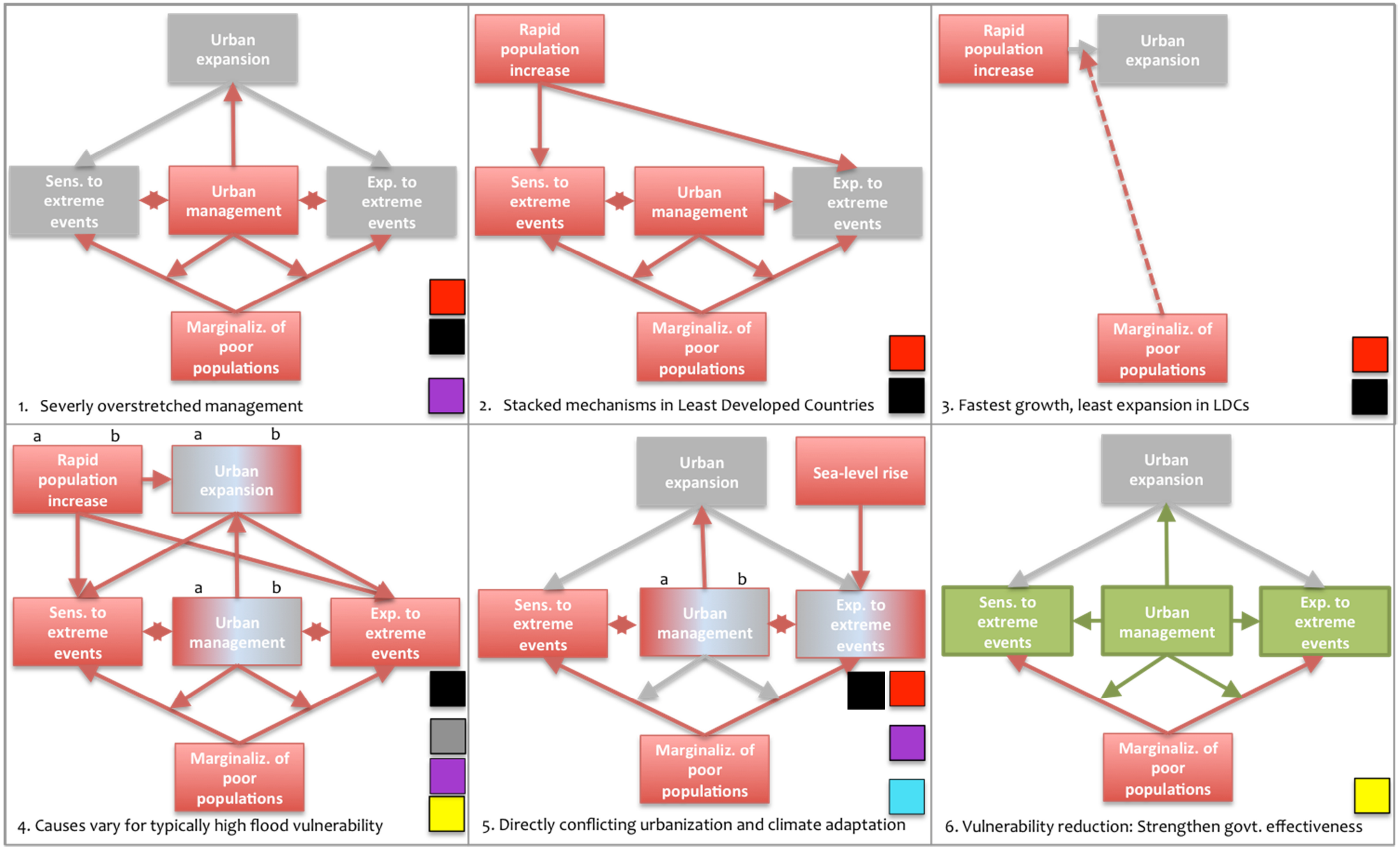

Figure 4.6: Six key socio-ecological vulnerabilities of urban populations under rapid coastal urbanization. Based on Figure 4.1 each diagram is a typical and particularly problematic combination and interplay of key vulnerability dimensions. Red boxes and arrows signify particularly problematic situations and influences based on indicator values, grey boxes signify less problematic situations and influences. Green boxes and arrows refer to entry points for vulnerability reduction. The number of each diagram refers to a corresponding subsection in the Discussion section. The colored boxes in the lower right hand corners indicate which urban vulnerability profiles each diagram applies to. LDCs stands for Least Developed Countries.

4.4.2 Vulnerability-generating mechanisms are dramatically stacked against coastal urban areas in LDCs (Group I profiles)

Inspection of all profiles shows that income and government effectiveness decrease with the rate of urban population growth, while urban poverty increases. The urban areas in group 1 (red Maumere and black Sittwe profile) exhibit both characteristics in extremis: They are simultaneously subject to the lowest income, most ineffective governments, most prevalent poverty, and world's most rapid coastal population growth rates (Figure 4.6, 2.). This makes is clear that vulnerability-generating mechanisms are dramatically stacked against the fastest-growing and most impoverished coastal urban areas in the world, which at the same time have the least adaptive capacity to reduce vulnerability. This applies to many LDCs along Western and Eastern African tropical coasts, Yemen, Pakistan, Myanmar, the Eastern Indonesian Archipelago, Solomon Islands, and Vanuatu (Maumere profile). In the Sittwe profile the situation is additionally aggravated by high levels of vulnerability to climatic extreme events: This means that urban areas in Madagascar, northern Mozambique, Small Island Developing States, Myanmar, and parts of the Philippines are subject to a "worst case reality" of well documented drivers of coastal urban vulnerability. In these areas hydro-meteorological climate extremes are not stopping rapid urban population increase**.** Klose and Webersik (2010; 2011) have shown that this is the case for population development and tropical storms in Haiti.

4.4.3 LDCs are the locus of the fastest but least expansive urbanization (Group I profiles)

Unsurprisingly, urban areas in all rapidly urbanizing coastal fringes are expanding. However, coastal urban population growth is most rapid where increase rates in urban area are slowest, i.e. in the red Maumere and black Sittwe profiles. The severe levels of slum population in these profiles suggest that the swell of inhabitants is largely absorbed on limited area by existing informal settlements and the erection of new ones (Figure 4.6, 3.). According to literature urban areas are generally increasing at twice their population growth rates (Angel et al. 2011), and population density is generally stagnating or in decline (Seto et al. 2011; Angel et al. 2011). On the other hand, none of the 30 representative cities Angel et al.'s findings are based on are located in the Maumere or Sittwe profile. Therefore, further investigation of population density change in these urban areas could nuance the ratio between area and population growth rates on the extreme end of the urban spectrum, i.e. for the fastest growing cities with high slum population levels.

4.4.4 High flood vulnerability is typical, yet a result of different combinations of causes (Sittwe and Group II profiles)

In the past, flood vulnerability in urban areas has been largely driven by socio-economic mechanisms: Noted causes include marginalization of the poor, ecosystem degradation, and poorly governed rapid urbanization (Ranger et al. 2011; Hanson et al. 2011; Revi 2008; Huq et al. 2007). By indicating each of these causes, as well as flood occurrence, damages, and adaptive capacity, this study shows two things: that severe values of these causes are typically combined to generate high flood vulnerability, and in which coastal fringes they co-occur.

For one, the noted causes co-occur in extremis in the impoverished black Sittwe profile in LDCs, as discussed in 4.2 (Figure 4.6, 4.a). These causes translate into large damages from floods, cyclones, or both. The causes also co-occur in all profiles of group 2 (grey Brus La Laguna, yellow Cebu, and purple Bluefields profiles). Here, however, high flood vulnerability is better explained by severe manifestations of different causes, namely the most rapid urban expansion rate and highest total of low-lying settlements (Figure 4.6, 4.b). This co-occurrence supports the finding that expansion is more rapid in the low-elevation coastal zone (Seto et al. 2011). In these profiles, we conclude that flood exposure is driven by large-scale flood-prone expansion into low-lying areas and rapid population growth. Flood sensitivity is driven by massive loss of wetlands (Figure 4.6, 4.). On the one hand, this causal combination can lead to particularly high flood vulnerability under low government effectiveness (Bluefields profile). On the other hand, the same causal combination leads to lower flood vulnerability under more effective government (Cebu profile). This is noteworthy, because in this profile occurrence of and damages from floods *and* cyclones are extremely high, and its low-lying areas along the subtropical coasts in Asia and Central America, the majority of The Philippines, China, Vietnam, Bangladesh and India (Bay of Bengal) are heavily populated.

4.4.5 Patterns of most rapid coastal development are in direct conflict with current and future climate adaptation (Bluefields, Muisne and Group I profiles)

Urban areas with the most rapid growth rates for population and urban expansion, respectively, are precisely the urban profiles other vulnerability-generating mechanisms are also most severe in. Based on this finding, it can be concluded that the spatial patterns of the most rapid growth rates for population and urban expansion circa the year 2000 are in direct conflict with vulnerability reduction efforts to climatic extreme events (Figure 4.6, 4.). This conflict can be expected to worsen under potential future increases in exposure and sensitivity to flooding and cyclones. We suggest that urban areas are particularly sensitive to future increases if their profiles exhibit a) very low current (circa the year 2000) exposure and adaptive capacity (Figure 4.6, 5.a), or b) high sensitivity (damage/occurrence ratio) (Figure 4.6, 5.b).

Case a) applies to the 51mn people in 41 countries (18% of the rapidly urbanizing coastal fringe) constituting the impoverished Maumere profile. Increases in exposure to flooding, e.g. due to climate change, may cause particularly severe managerial problems: The very low occurrence level circa the year 2000 and very low adaptive capacity suggest high damages once exposure increases. This situation is not acting as an early warning signal for potential future increase in damages due to sea level rise, storm surges, and pluvial and fluvial flooding. Case b) applies to 196mn people in 58 countries (38.5% of the rapidly urbanizing coastal fringe) in profiles with low and high income levels - the Bluefields profile, Sittwe and Muisne profiles. Currently, low to moderate occurrence in these profiles already translates into similar damages observed under much higher occurrence in other profiles. This suggests a low capacity for climate-related disaster prevention or post-disaster management. This deficiency is particularly concerning, because ongoing sea level rise is co-occurring with high values of rapid growth, urban poverty, and low-lying settlement.

4.4.6 Building on government effectiveness and experience provides entry points for vulnerability reduction (Cebu profile)

Generally speaking, it is critical for LICs and MICs is to reduce risks from climate change to urban areas through mindful and integrated strategies for urban land-use planning, channeling settlement, and climate adaptation (Satterthwaite 2009). In this context, Huq et al. (2007) indicate that pro-poor urban climate adaptation policies are needed. These policies are particularly effective under the involvement of households, communities, but also various levels of government (UN-HABITAT 2011). Measures of upgrading informal settlements through collective organization have shown potential to reduce vulnerability to extreme climate events in multiple African and Asian cities (Revi et al. 2014).

Ideally, jointly enhancing a) the adaptive capacity of flood-sensitive slum populations and b) the effectiveness of government-led reduction of exposure and sensitivity would benefit all flood-vulnerable profiles (Group II and Muisne profiles, Figure 4.6, 6). A conceivable strategy for reducing the causes of severe exposures is diverting extremely rapid urban expansion from heavily populated, and remaining unpopulated, risk-prone low-lying areas. Likewise, a conceivable strategy for reducing a cause of severe exposures is to protect the limited remaining wetlands from further encroachment. Another effective response is the community-based initiative “Homeless People’s Federation of the Philippines” (Carcellar et al. 2011; Revi et al. 2014). If pronounced social disparities indicate poor top-down organizational abilities to implement such measures, such as in the Muisne profile, or governments lack resources or political will, collective organization in the affected communities may be a more promising way to reduce vulnerability (De Sherbinin et al. 2007).

4.4.7 Discussion of the method

We used the most recent and best available datasets referring to the year 2000 as a for our analysis between 2010 and 2015. We selected the year for analysis (approx. 2000) based on the most recent time frame for which all of the georeferenced indicator datasets were available. Some of these indicator datasets have not been updated to later time frames. The common time frame was the basis for this first approximation of the recent situation of coastal vulnerability of urban populations under rapid urbanization. The common time frame also avoided retro-causality between temporally diverging indicator datasets.

We recognize that new datasets have become available in recent years for some, but not all indicators. The 2009 Global Assessment Report on Disaster Risk Reduction has since superseded the data from Dilley et al. (2005) on floods and tropical cyclones by offering a higher resolution and improved modeling of risk frequency and severity (UNISDR 2009). However, the data stems from 2007, therefore representing a decadal time frame for which more recent global data on wetlands prevalence, government effectiveness, urban population change, urban area change, and slum population level was still lacking. Hence, we have not included some newly emerging datasets, because a complete indicator set in a common time frame provides for a more useful baseline study. Furthermore, a newer version of the Gridded Population of the World (GPW) v.4 dataset was published in 2016 (CIESIN 2016) after this analysis was completed.

Our results can be interpreted as a first-order approximation of commonalities and differences in vulnerability between rapidly urbanizing coastal areas based on recent, most complete available data at the time of analysis. This approximation provides the missing baseline for analyzing in how far the patterns of vulnerability change over time. This baseline study motivates a follow-up analysis of the dynamics of vulnerability generation of urban populations as soon as more recent data for all indicators is available. The follow-up can be also based on projected data from an integrated assessment model such as IMAGE. In proof of this concept, Lüdeke et al. (2014) have already analyzed changes in the typology of smallholder vulnerability to global environmental change in global drylands using projected data from IMAGE.

Like all statistical analyses this study comes with its limitations. The first limitation is the specificity of an indicator, which can show a large spread around its cluster center value (i.e. stretched central quartiles, see Figure 4.4). This means that the cluster membership of a grid cell may not say much about each specific indicator. In this case it is important that the cluster center value of such an indicator does not play a decisive role in the interpretation of the cluster or profile group it belongs to. A second limitation is that our results do not distinctively address specific urban agglomerations, or cities, according to their administrative boundaries, bur rather grid cells. The reason for this design is clear: It is not feasible to unambiguously assign all comparable subnational data to rapidly urbanizing coastal cities globally. The third limitation is the use of national-level data when subnational data was either unavailable (e.g. for government effectiveness), or unfeasible (for GDP per cap), for capturing local or regional vulnerability-generating phenomena in urban areas. At the same time, national level GDP per cap differentiates between LICs, MICs, and HICs. This can help indicate the resources a national economy can mobilize for vulnerability reduction, e.g. for climate change adaptation (Revi et al. 2014). We ruled out using the subnational dataset of ‘‘gross cell product’’ per cap (Nordhaus 2006), because numerous coastal countries with rapid growth lack the data.

4.5 Conclusions

We developed and discussed a global spatially explicit systematization of typical mechanisms that generate coastal urban vulnerability under rapid urbanization. The systematization is for the year 2000. The results show that typical combinations of these links exist, and where they occur, regardless of whether a case study exists in this particular location or not. On a global scale, the results advances the knowledge of links between typical socio-ecological problem structures and vulnerabilities in coastal urban areas under rapid urbanization in LICs and MICs. On a regional to a more local level the results show that local vulnerability-generating mechanisms recurrently formulated in city-based case studies can be robustly identified across coastal regions.

Generally speaking, income and government effectiveness decrease with the rate of urban population growth, while urban poverty increases. Furthermore, we underlined the criticality of flood occurrence and damage in shaping coastal urban vulnerability under rapid growth in LMICs. Cyclone occurrence and damage, and government effectiveness, are also important. There are huge asymmetries between profiles regarding vulnerability and how they are positioned to deal with and reduce vulnerabilities. This is the case in many LDCs along Western and Eastern African tropical coasts, for example. Spatial patterns of the most rapid growth rates for population (two profiles) and urban expansion (three profiles) in direct conflict with vulnerability reduction efforts to climatic extreme events for 247mn people in 75 countries (18% of the rapidly urbanizing coastal fringe). This conflict can be expected to worsen under potential future increases in exposure and sensitivity to flooding and cyclones. In order to reduce risk, which is the critical issue for climate adaptation in LICs and MICs (Satterthwaite 2009), this calls for a mindful, integrated, and effective approach of urban land-use planning together with climate adaptation.

On a generic level this typological approach may facilitate learning and scaling up successful place-based vulnerability reduction in areas of the same profile, i.e. areas with similar socio-ecological problem structures. Thereby the hypothesis is that a similar problem structure suggests comparable intervention options, i.e. that the typology of adaptation needs may be a typology of adaptation responses. This hypothesis has been corroborated by Kok et al. (2015) and Sietz et al. (Sietz et al. 2011), yet needs to be explored further in an urban setting. Under limited funds, time, and human resources available for vulnerability reduction in our time this could aid in the urgently needed replication, and upscaling of vulnerability-reducing measures that were successful in a certain urban context, across specific urban profiles.

The urban profiles identified in this study can also be useful for increasing the understanding of other societal outcomes that are conceivably related to the coastal vulnerability of urban populations, such as conflict incidence. Already, a study based on the same methodology applied here has increased the understanding of how violent conflict incidence and distribution is linked to typical socio-ecological problem structures in a global typology of drylands vulnerability (Sterzel et al. 2014).

Follow-up studies should analyze changes in urban profiles relative to the baseline of this study. We recommend prioritizing the use of the most recent common time frame that all required datasets are available in over simply including the most recent, best available data. Furthermore, studies should analyze the dynamics of the urban vulnerability profiles, and what this means for future risk management, using projected socio-economic and environmental change data from integrated assessment models.

Using the same methodology, Lüdeke et al. (2014) have already conducted such a study for detecting and understanding change in profiles of drylands vulnerability.

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5 Discussion and Conclusions

Chapter 1 put the overarching research question RQ1 into context. Using the refined methodology introduced in Chapter 2, vulnerabilities of human populations to multiple socio-ecological and environmental stressors are subsequently analyzed in Chapter 2 (“Drylands”), Chapter 3 (“Conflict”), and chapter 4 (“Urban”). In chapter 1, the sections 5.1 and 5.2, 5.3, and 5.4 each deliver specific answers to the corresponding research questions RQ 2, RQ 3, and RQ 4. The outcomes enable us to provide a detailed answer to the RQ 1:

RQ 1) How can socio-ecological vulnerability of human populations in specific systems with global distribution be reduced in complexity to identify generic local and regional adaptation needs, given the lack of financial and human resources to locally assess all places in need?

Section 5.6 critically reflects on lessons learned in the research process for this dissertation, and on remaining shortcomings. Section 5.7 draws the conclusions of this dissertation.

5.1 Methodological Advancements

GEC research has repeatedly shown that local and regional case studies across the globe often share similar combinations of causes for vulnerability in a given socio-ecological system. We applied data driven clustering methods followed by some statistical methods to identify such combinations in the data structure. To address RQ 2, the methodological advancements we made compared to the literature are discussed in the following subsections, while the content-related advancements are discussed in Section 5.2.

RQ 2) How can a spatially explicit methodology used for globally systemizing typical causes of socio-ecological vulnerability of human populations in drylands be refined to be applicable to any socio-ecological system, and how can its application benefit vulnerability reduction?

5.1.1 Analyzing Vulnerability Patterns in any Socioecological System

Previous to this dissertation, Sietz et al. (2011; 2011) already applied a methodology for globally systemizing typical causes of vulnerability in one specific socio-ecological system, i.e. drylands. Using the same socio-ecological system, we refined their methodology to globally systemize typical causes of vulnerability in any socio-ecological system. We broke the methodology down into four steps. Each step answered a specific question. To allow for better uptake of the methodology in the scientific community, we aligned its principle structure with well-established guidelines for vulnerability assessments of socio-ecological systems under global change (Schröter, Polsky, et al. 2005).

Step 1: Defining a relevant and distinct socio-ecological system for vulnerability analysis. The question this step answers is: *“What are the main exposures, key vulnerable groups, their sensitivities and coping and adaptive capacities in a specific socio-ecological system?”* We answered this question based on previous global typologies of key vulnerabilities of smallholder farmers in drylands (Janssen et al. 2012; Kok et al. 2010; Sietz 2014). Drylands occupy approximately one third of Earth’s land surface, and the system boundaries of drylands were well defined by thresholds for rainfall and evaporation (Safriel et al. 2005, 2008).

Step 2 Identification of core dimensions and indicators. The question this step answers is: *“What are the core dimensions of the patterns of vulnerability occurring in the socio-ecological system under investigation?”* The factors typically shaping vulnerability in drylands were identified using the extensive case studies reviewed by Jannsen et al., Kok et al., and Sietz et al. (2012; 2010; 2014). These factors were human well-being, pressure on resources, connectedness, natural resources, and overuse (Table 2.1). Seven datasets with global coverage and subnational resolution (0.5° lon x 0.5° lat) were then determined as indicators for these factors (GDP per capita, infant mortality rate (IMR), population density, road density, surface water run-off, grassland productivity, and water-based soil erosion). Based on further literature review, we added two new indicators, which were unaccounted for until now: income and population density.

Step 3 Identification of vulnerability profiles and their spatial distribution. The question this step answers is: *"In which regions do we find similar vulnerability characteristics (vulnerability profiles)?"* To answer this we refined and applied an elaborate cluster analysis from Janssen et al. (2012) for analyzing socio-ecological systems, using the seven identified indicator datasets. Each of the resulting eight drylands vulnerability profiles (clusters) linked a typical combination of causes (Figure 2.1) to where they occur in drylands (Figure 2.2). This resulted in a spatially explicit systemization of socio-ecological vulnerability in drylands. The revisions we made to the cluster and sensitivity analysis are discussed in the following subsection.

Step 4 Interpretation and verification of vulnerability profiles. The question this step answers is: *"What do the different vulnerability profiles signify in terms of vulnerability creating processes?"* We interpreted and verified the eight profiles constituting the typology. Thereby we focused on profiles in LMICs, where funds and resources for vulnerability reduction are usually more constrained. Using the refined methodology produced a more nuanced and differentiated typology in comparison to the state-of-the art by Sietz et al. (2011). The content-related improvements are discussed in Section 5.2. Testing the plausibility with an additional eight case studies substantiated these results (see list of case studies in the Annex, Table 8).

5.1.2 Cluster Analysis and Sensitivity Analysis

For the actual clustering we combined two well-established clustering algorithms – one hierarchical, and one partitioning algorithm. We used the computationally attractive K-means clustering algorithm for partitioning the data points into K groups (Mac Queen 1967). The results of using K-means to identify the 'optimal' partitioning are sensitive to the data starting points of the search process, expressed by partitioning into local minima. Therefore, we chose the Ward method (Ward 1963), a hierarchical clustering algorithm, for delivering the initial starting points for K-means based on a subset of the data. Milligan (1980) showed the good performance of this approach for this purpose. Further details on the clustering can be found in the Annex.

Regarding Step 3 in the methodology, we made multiple improvements to the clustering, and to analyzing its results, employed by Sietz et al. (2011). We used a combination of methods to determine the most suitable number of clusters, which is a central step in any methodology based on clustering. We determined the most suitable number of K clusters to partition the dataset into, based on the notion of cluster stability (Ben-Hur et al. 2002; Roth et al. 2002). This also determined the sensitivity of the partitioning to local minima of K-means. We calculated a measure of consistency, or sensitivity, for each K by comparing the variation between pairs of cluster partitions. The pairwise comparison was repeated 200 times with changing initial conditions (i.e. different starting conditions, and perturbation or resampling of the data).

Clustering outcomes can also be sensitive to the scaling of the data. Therefore, we performed a recommended min-max normalization to rescale the data to values between 0 and 1 before using K-means

(Milligan et al. 1988). Each normalized indicator dataset was fed in to the cluster analysis with the same weight of 1.

Turning to Step 2 (Identification of core dimensions and indicators) and Step 3 (Identification of vulnerability profiles and their spatial distribution), we added a number of methods to further improve sensitivity analysis in the methodology. These included data exploration techniques for a) selecting the optimal number of clusters, b) determining the importance of each indicator dataset for the clustering process, and c) interpreting the resulting vulnerability profiles.

From the consistency measure for each K we produced a consistency graph across Ks to identify a local 'optimum' cluster number (see Annex, Figure A1a). In case the consistency graph does not display one local optimum we supplemented the selection of the 'optimal' number of clusters for various K with a branching diagram (see Annex, Figure A1b). This is novel compared to previous work using this measure (Sietz et al. 2011; Sietz 2011), and was important for two reasons: First, it suggested an appropriate level of detail for striking a balance between spurious and accidental detail (large K) and obvious, uninformative groups (small K). Second, it provided information on the relationships between clusters for various numbers of K. Therefore it showed which clusters were (in-) discernable across various numbers of K, thereby revealing particularly robust (or instable) structures in the data space.

It is crucial to obtain information on the importance of each indicator dataset for the clustering process, i.e. for shaping the entire vulnerability typology. Therefore, we included a new measure in the methodology - the Fraiman index (Fraiman 2008) - which determined how sensitive the clustering results were to omitting each indicator dataset from the process (see Annex Figure, A1c). In recent studies, the importance of each indicator was determined through the variance using Principal Component Analysis (PCA) (Sietz et al. 2011; Sietz 2011). The resulting principal components explain a sufficient degree of the variance within the data space. However, this is a linear approach addressing the whole data space, and it is insensitive regarding structures along one principal axis, i.e. the most important axis there may or may not be a cluster separation along. The Fraiman measure, on the other hand, explicitly addresses this kind of structure. Therefore, it was the more appropriate method for determining indicator importance in our context.

Adding boxplots for each of the indicator value distributions in each cluster allowed for a more in-depth examination of each cluster's specificity, value distribution, and overall interpretational power (see Annex Figure A1 d for details). This allowed for more nuanced statements about each clusters' characteristic features, how (in-) distinct clusters are in the data space, and how (in-) distinct indicators are in each cluster.

Overall, the above methodological improvements in Step 2 and Step 3 (identification of robust vulnerability profiles) made the methodology more applicable to any given socio-ecological system, and to explore any given socio-ecological system, because the methodology now provides the appropriate level of detail to give an answer to the penultimate sensitivity analysis: whether or not the vulnerability profiles made sense. In addition, the clusters were more easily interpretable and verifiable than an aggregated index, because their basis remained explicit and traceable through Step 2, Step 3, and Step 4.

5.1.3 Scenario Analysis

In order to reduce vulnerability in any location, the first step is to understand the present situation. Since vulnerability to GEC is dynamic in nature and varies over time (Füssel 2007), the question arises how our typologies of the present, or near-present, situations in drylands, the RUC, and violent conflict in drylands can be used for assessing change. We addressed this question by assessing and comparing global policies with regard to their impacts on specific vulnerabilities on the regional/local scale (Lüdeke et al. 2014): Using our methodology we analyzed changes in the typology of smallholder vulnerability to GEC in global drylands between the baseline and 2050. We applied indicator scenario data from the integrated assessment model IMAGE (Alkemade et al. 2012) using climate policy scenarios of the OECD Environmental Outlook (OECD 2012), and environmental policy scenarios from GEO 4 (UNEP 2007). In one approach, we compared the resulting typologies in 2050 to the baseline typology ("time slice analysis"). In the more complex second approach we determined which locations were present in a similar situation *and* were projected to undergo a similar change in vulnerability in the future ("clusters of change analysis"). This approach turned out to be particularly useful for evaluating different indicator scenarios when the scenarios showed significant differences. However, it showed limitations when scenarios only differed slightly. Change analysis for vulnerability patterns can contribute to future policy analysis in such ways, and this needs to be explored further.

5.1.4 Analysis and Plausibilization of Socio-ecological Vulnerability across Spatial Scales

We acknowledge that it is crucial to identify and analyze relationships at different spatial scales for the analysis of socio-ecological systems (Ostrom 2009). We show different scale-dependent ways of how our methodology accommodated for this requirement in the following.

We integrated findings from both local and regional-scale case studies within a well-defined socio-ecological system in Steps 1 and 4. We determined the main exposures, vulnerable groups, sensitivities, and adaptive capacities within this system. For example, a case study of Rio de Janeiro from De Sherbinin et al. (2007) identified linked causes of vulnerability to floods: A combination of high flood exposure, rapid urban expansion into flood-regulating natural floodplains and wetlands, and prevalent settlement in low-lying areas, led to high flood damages in Rio. We identified this combination in other case studies in Step 1, and again in a vulnerability profile in Step 4: Rio de Janeiro was correctly member of this profile (see Figure 4.1 and Figure 4.2). In Step 4, we used local and regional-scale case studies for plausiblizing each vulnerability profile and its spatial distribution. Thereby we tested whether each profile reflected characteristics from studies within this profile. This was important for determining whether the global assessments had explanatory power on the local and regional scale, apart from the global scale. Overall, we used 34 local and regional studies to plausibilize the profiles in drylands, violent conflict incidence in view of the drylands profiles, and the profiles in the RUCF (see Annex for a list of these case studies): The good agreement of our results with results from the studies on each spatial scale, and the absence of contradictions, increased confidence in our methodology.

We drew from regional-scale analyses (maps, case studies) in Step 4 to interpret the spatial distribution of profiles. Apart from further plausibilization, this led to a better understanding of both vulnerabilities, and reduction measures, in the profiles. For example, a comparison of profile distributions with irrigation and livestock production system maps explained predominant soil erosion causes in HIC profiles, i.e. from cropland irrigation (light lilac profile, see Figure 2.1 and Figure 2.2), or overgrazing (dark lilac profile). Large rivers (black profile) and loess soils (blue profile) allowed for a nuanced, profile-specific interpretation of overuse and human-wellbeing under high natural resource endowment. Finally, using case studies on the success of soil erosion prevention measures across locations in Ethiopia and Eritrea (Herwig et al. 1999), we found that the profile membership of these case study locations was helpful to understand, and predict the success of prevention measures: Conservation measures showed much greater reduction in soil erosion rates in the grey profile locations than in blue profile locations (see Figure 2.1 and Figure 2.2).

Finally, global-scale analyses supported all four steps. This included defining a distinct socio-ecological system of global relevance, identifying the typical causes of vulnerability using case studies throughout the system worldwide, quantifying these causes with datasets with global coverage, and interpreting and verifying globally distributed vulnerability profiles.

5.2 Advancements in the Typology of Drylands

The application of our improved methodology led to improved results in comparable existing drylands analysis. We confirmed the key tenets of the typology structure from Sietz et al. (2011). We confirmed the existence of two basic groups of profiles in the typology with regards to human well-being. Human well-being was indicated by average income and IMR. All drylands in high-income OECD countries (USA, Spain, Italy, Australia) were systemized by two profiles with highly favorable values, while all drylands in LMICs were systemized by the other profiles (six, and five for Sietz et al. (2011) Figure 2.1).

However, our results in LMICs were also a comprehensive step forward. The key difference of our typology to Sietz et al. (2011) was the addition of, and increased differentiation in profile narratives in drylands in LMICs. This was possible by including two additional indicators and newer datasets in the cluster analysis, and the subsequent interpretation of resulting profiles. Based on further review of case studies, we included datasets of population density and GDP/cap. Population density was instrumental to quantify the demand of and pressure on water resources. GDP/cap was used to quantify income as a further variable for the crucial vulnerability dimension of human well-being. The newer dataset for agropotential from 2006 (as opposed to 1996) showed a much more differentiated value distribution in the profiles. The road density dataset from 2009 was also more differentiated than in 2001.

As a result, these advancements led to a more realistic global overview of socio-ecological vulnerability in drylands. We were able to identify two natural resource-rich profiles in LMICs, which were subsumed in other profiles in Sietz et al. (2011). The key features of the resource-rich profiles (green and black) were overpopulation on medium and high resource endowment, which resulted in medium or high soil erosion, under low income. Under the highest availability of surface water run-off and high agropotential, very dense population led to extremely degraded soil, which explained low to moderate levels of human well-being. Population density and soil degradation were extremely high in the green profile (India, north-eastern China, Nile basin), and moderate in the black profile (lower courses of the Indus, Euphrates, Tigris and Volga, further irrigated areas such as the Aral Sea basin). Both profiles showed good agreements to case studies, confirming that the new typology features were also meaningful. For example, high income and high infant mortality suggested high disparities regarding socio-economic opportunities, and access to the abundant water resources, in the black profile. This was confirmed by Mustafa and Qazi (2007) in the Indus Basin, showing that replacement of sustainable, traditional irrigation systems through groundwater pumping led to increases in social disparities and to the degradation of natural resources.

Finally, we made the differentiation within the typology more explicit and accessible for the reader by grouping and naming the profiles based on similar characteristics. In LMICs, the six profiles were paired into three groups according to resource-constrained, less constrained, and rich endowment, while each pair itself was distinctly separable through varying configurations of human well-being and overuse.

An explorative comparison of how successful the same adaptation measures were in different clusters showed cluster-specific responses to these measures. In the highlands of Ethiopia and Eritrea, for example, cluster membership distinguished between soil erosion reduction rates of different conservation measures in agricultural plots located in the closely related grey cluster (low water availability, average soil quality, less populated) and blue cluster (low water availability, average soil quality, more populated)

(Herwig et al. 1999). Soil erosion reduction for different conservation measures was much higher in the grey cluster, and in one case soil erosion increased in the blue cluster. Therefore, cluster membership was helpful to understand the degree of success of adaptation measures, or even failure, in specific clusters. Overall, all drylands across the globe were systemized according to similar problem structures causing vulnerability. The example from above showed that these problem structures also hint at similar responses to adaptation measures. Therefore, the typology may benefit vulnerability reduction further if it is substantiated as a typology of adaptation measures.

5.3 Violent Conflict Distribution Through the Lens of Drylands Vulnerability

We found that a limited number of typical problem structures in drylands plausibly systemized socio-ecological vulnerability (Chapter 2). This typology was derived by clustering key factors causing vulnerability: natural resource endowment, poverty, and overuse-related factors (Table 3.1). Literature on violent conflict showed that these causes of socio-ecological vulnerability were conceivably linked to human security in drylands as well. Answering RQ 3 aims at increasing the understanding and spatial patterns of these links.

RQ 3) Does a global typology of typical causes for socio-ecological drylands vulnerability involving resource scarcity, overuse, and poverty-related factors increase the understanding of what drives violent conflict?

To answer this question, we conducted spatial and statistical data analyses of our typology of socio-ecological drylands vulnerability (0.5° long x 0.5° lat) and point data for violent conflict locations. A spatial overlay revealed that drylands (46 conflicts) were just as prone to conflict as non-drylands (70 conflicts) with respect to land area. This cast initial doubt on a mono-causal explanation of conflict onset through water scarcity (Figure 3.1). Since there was no conflict incidence in HICs (two profiles), we focused on LMICs (six profiles), where all conflicts in drylands were located. These conflicts revealed a heterogeneous spatial distribution that corresponded to the distribution of our socio-ecological vulnerability profiles in the typology: All 46 drylands conflicts were located in four out of six profiles in LMICs, while two profiles showed no conflict (Table 3.3).

How did our typology based on clustering fare in explaining conflict incidence and absence compared to conventional mono- and multivariate regression models? For a quantitative answer to this question, we used two well-established statistical measures for selecting the preferable model – the AIC and ROC. In the first case, the *quality* of the cluster-based model was significantly better than any conventional mono- and multivariate regression model of the indicator datasets using the AIC (82 compared to 102 from the best multivariate regression model – the smaller the value, the better (Akaike 1974)). Second, using the ROC we showed that the *capability* of the cluster-based model of *predicting* conflict incidence and absence in areas significantly outperformed the conventional approach (ROC, 0.74 compared to 0.55 – 1 being a perfect classification, and 0.5 being random guesses).

We created an index for comparing the explanatory power of each model using the same indicator data. The index was not used for ranking vulnerability after far-fetched aggregation (see 1.2.1), but rather to make the two models comparable. The non-linear cluster-based model (one 7-dimensional dataset) explained violent conflict incidence significantly better than the mono- and multivariate logistic regression models (1 to 7 datasets). The latter two are conventionally used in peace research (Benjaminsen 2008; Buhaug 2010; Meier et al. 2007) (Figure 3.2, Figure 3.3).

There are multiple quantitative reasons for the advantages of our approach. First, our cluster-based approach (a non-parametric approach) does not bind the data to a prescribed functional form: No deterministic relationship is assumed between the indicator datasets in the sense of a function class, e.g. through multilinear or quadratic functions (parametric approaches). Furthermore, our cluster-based approach allows for dependencies between these variables to explain conflict incidence. The multivariate regression models explicitly lack this characteristic. Within the wealth of environmental change-related peace research it is very rare to objectively identify preferable conflict models with the well-established AIC and ROC measures, with some exceptions e.g. (Buhaug et al. 2015; O'Loughlin et al. 2014, 2012; Wischnath et al. 2014). We suggest utilizing these measures more in the future.

Importantly, there were also qualitative reasons for the quantitative statistical advantage of the cluster-based model. These reasons became evident through systematic qualitative interpretation of the four profiles showing conflict and the two profiles showing none. The interpretation was guided by the typical value combinations of indicators in each of these profiles. We found that conflict neither generally increased with resource scarcity nor with overuse (Figure 3.4). We reached a systematic and robust explanation of conflict incidence and absence throughout these profiles with the importance of poverty-related factors and resource overuse depending on the levels of natural resource endowment. In other words, different socio-economic variables determined conflict incidence depending on the levels of resource endowment. This meant that the dependence of conflict incidence on environmental and socio-economic variables, and the dependence of socio-economic variables on environmental variables, was non-linear. These types of relationships are irreproducible with linear models commonly used in peace research, e.g. linear regression, or mono- and multivariate logit models. Therefore, we were able to show that

a) mono-causal and blanket statements do not capture the conflict causes in drylands;
b) neither the "neo-Malthusian" position of purely resource-scarcity-induced conflict (Homer-Dixon 1991) nor the "neo-Durkheimian" position of purely socio-economically-induced conflict (Shaw et al. 1987) explain what drives violent conflict in drylands; and
c) an unconventional way of combining datasets can advance this ongoing discourse.

Most importantly, we achieved the most robust insights into what drives conflict in drylands through a non-linear combination of indicators for environmental and social factors. This made it possible to reproduce existing systematic interdependencies between environmental and socio-economic factors.

We verified the profile-specific explanations of conflict incidence using five local and regional case studies from the literature: in the conflict-intensive drylands sample of choice in Ethiopia, Eritrea, Somalia, and Djibouti (Berhe et al. 2007; Getachew 2001; Markakis 2003; Rettberg 2010; Raleigh et al. 2006). Each case was related to resource scarcity and violent conflict (see list of case studies in Annex, Table 8, for plausibilization details). All three profile narratives, and explanations for conflict through combining natural and socio-economic causes, were well in line with the case study literature - despite the absence of strictly political indicators in our study. A further step forward in analyzing violent conflict in drylands will be to include political indicators in the clustering approach.

In profiles with similar endowments, conflict generally increased with lower endowment and/or more overuse. In countries with low and high endowments, conflict was absent when less overuse converged with higher human well-being, i.e. less poverty and higher income. Going beyond other studies, we calculated indicator value thresholds and ranges for conflict-free situations. The most severe conflict-free averages for income and poverty-related factors were USD 2995 for GDP/cap, and an infant mortality of 43 deaths per 1000 live births. The highest conflict-free averages of overuse were a water erosion index of 0.177, and a population density of 79 people per km^2. The lowest averages of resource endowments without conflict were a water runoff of $10.3*10^3 m^3/(yr*km^2)$, and an agropotential of 0.005 KgC/m^2 (i.e.

kilograms of carbon when cultivating grassland, drylands range from 0 - 0.55 KgC/m²). We suggest that using such thresholds and ranges more in the future will make cross-study comparisons of conflict-free situations easier.

Violent conflict is a societal outcome with conceivable links to drylands vulnerability through resource scarcity, overuse, and poverty-related factors. Yet the concept of socio-ecological vulnerability is currently seldomly used in this field of research. We showed that our causal and spatial patterns of drylands vulnerability provided systematic, differentiated and robust explanations for violent conflict incidence in drylands. The data-driven vulnerability framework we employed proved to surpass conventional methods in increasing the understanding of what drives violent conflict, and how. Therefore, our analysis was able to make a useful contribution to the ongoing discourse about the significance of natural resource-based causes of violent conflict. We suggest further applications of such a framework in the future to analyze violent conflict onset and distribution.

5.4 Typology of Coastal Vulnerability under Rapid Urbanization

Unprecedented urbanization is forcing coastal cities with limited resources throughout LMICs (and some HICs) to tackle emerging socio-ecological problems together with long-standing ones. This is a fundamentally difficult task for urban management. We systemized typical combinations of these problems to answer RQ 4, i.e.

RQ 4) What are causal patterns of socio-ecological vulnerability which are typical for urban populations in the context of rapid coastal urbanization, and how are they positioned to deal with these vulnerabilities?

We produced the first spatially explicit and global overview of typical socio-ecological vulnerabilities of urban populations under rapid coastal urbanization. For this we applied a formalized cluster analysis-based method (Kok et al. 2015; Janssen et al. 2012) on data indicating 11 causes of socio-ecological vulnerability typically formulated in local and regional studies (see Table 4.1). Importantly, testing the plausibility of the overview with an ample body of 21 studies and case studies substantiated the well-aligned results (see list of case studies in Annex, Table 8, for details).

We calculated global figures of rapid coastal urbanization using GIS analysis, which were missing in the literature to date. Urban areas experiencing rapid population growth (defined as above average, i.e. >2.25% annual increase of urban population according to UNDESA 2008) were home to a quarter of the world's urban population (Table 4.2). Rapid urbanization was underway in 55% of the world's countries with a coastline (84 out of 153), and in 43% of all countries (196). It is well-documented that rapid urbanization is overwhelmingly a phenomenon of LMICs (Satterthwaite 2007; The World Bank 2010). We went a step further and showed that rapid *coastal* urbanization is as well.

By using largely subnational indicator data for the causes we produced a more nuanced spatial overview than valuable older studies of unbalanced urbanization using national-level data (Lüdeke et al. 2004; Kropp et al. 2001). We also produced a more differentiated structural overview: Cluster analysis showed that robust structures did in fact exist in the data space of 11 indicators. Each of the seven distinct clusters, which we labeled urban vulnerability profiles, resembled a similar structure of causes of vulnerability (Figure 4.2). Each vulnerability profile has a spatial distribution, spanning multiple locations and regions (Figure 4.1). Analysis of the profiles advanced the knowledge which typical combinations of causes of vulnerability occur, and where they occur. The following key results confirmed or advanced the literature.

First, we confirmed that high exposures and sensitivities to climatic extremes were critical in shaping the typology of urban socio-ecological vulnerability under rapid growth in LMICs, and particularly in LICs (Satterthwaite 2009). Our analysis underlined the criticality of flood exposure and sensitivity in LMICs. High flood vulnerability was evident in four profiles amounting to 50% of all rapidly urbanizing coasts, in 54 out of 84 countries (64%) for 451mn people (19% of the global urban population). Yet while high flood vulnerability was typical, the profiles showed that it resulted from different typical combinations of causes, which would be obscured with conventional index-based approaches: Flood vulnerability in urban areas has been largely driven by socio-economic factors such as marginalization of the poor, ecosystem degradation, and poorly governed rapid urbanization in the past (Hanson et al. 2011; Huq et al. 2007; Ranger et al. 2011; Revi 2008). Going beyond studies without an integrated treatment of these causes, we showed that the impoverished black Sittwe profile linked all of these causes to *where* they actually occur in severe forms: e.g. in small and middle-sized cities in Least-Developed Countries (LDCs) in Madagascar and Mozambique (Toamasina, Angoche), Myanmar (Sittwe), the Central Philippines (Tacloban), Belize (Belize City), and South Pacific Small Island States (Labasa). In other profiles, high flood vulnerability was best explained by the most populous urban settlement of low-lying areas and most rapid urban expansion in coastal areas according to the indicator values (despite large damages from floods, cyclones, or both): Large-scale flood-prone urban expansion into low-lying areas and rapid population growth caused the high exposure to flooding, while the resulting massive loss of wetlands caused high flood sensitivity. This supported the finding that urban expansion is more rapid in low-elevation coastal areas than elsewhere (Seto et al. 2011). As a next step, we suggest to include urbanization rates of different city sizes in the cluster analysis and to compare the results to existing vulnerability analysis on a national level (Birkmann et al. 2016).

Second, tropical cyclones, coastal flooding, and rapid urban population growth were typically combined. This was characteristic for five urban vulnerability profiles, each showing a high sensitivity to cyclones, floods, or both (38.5% of the rapidly growing urban coast, 196mn people, 6.8% of the global urban population in 58 countries). We were able to show - beyond local case studies and across continents - that climatic extreme events do not appear to be stalling rapid population growth or urban expansion in risk-prone coastal areas. Klose and Webersik (2010; 2011) demonstrated this for tropical cyclones and population growth in Haïti over time. This development is a clear reason for concern for overstretched urban management in these regions, because im many regions frequency and magnitude of climatic extreme events are expected to increase through climatic change.

Third, we found that urban management is indeed severely overstretched in a third of the RUCF. This is the case for three profiles (Sittwe, Maumere, and Bluefields profiles) with 145mn people in 57 countries. Adding the less severely overstretched Cebu profile increases the numbers to 47%, and 294mn people in 58 countries. These profiles showed a good agreement with the spatial distribution of the highest two (out of five) classes of urban vulnerability to natural hazards on a national level by Birkmann et al. (2016). However, our profiles added a more differentiated subnational picture of causes. Global change vulnerabilities can outpace vulnerability reduction in rapidly growing LICs and MICs (O'Brien et al. 2012; UNISDR 2011). If overstretched management is a proxy of this risk, then the key implication of our finding of typically severely overstretched management in the coastal fringe is clear: Vulnerability reduction is being, or risks being, severely outpaced in up to half of the RUCF.

Fourth**,** we showed that causes of vulnerability and the fewest means to reduce vulnerability were dramatically stacked against urban areas in coastal LDCs (24.9% of the RCU; 48 countries, 66.3mn urban inhabitants): Two profiles subsumed the fastest coastal urban population growth worldwide, the lowest income, most ineffective governments, and most prevalent poverty (4.2.). The first profile (red Maumere profile) summarized LDCs with little to no exposure to cyclones and flooding along Western and Eastern African tropical coasts, Yemen, Pakistan, Myanmar, the Eastern Indonesian Archipelago, Solomon Islands, and Vanuatu. In the second profile (black Sittwe profile) the situation is additionally aggravated by high levels of vulnerability to climatic extremes, which mainly consists of small and medium sized cities (spatial distribution as noted above, Figure 4.1, Figure 4.2): This profile subsumes a "worst case reality" of well documented drivers of coastal vulnerability of urban populations. Again, this added differentiated subnational detail to recent literature findings on a national level: Birkmann et al. (2016) had shown that low adaptive capacity and high overall vulnerability to all types of natural hazards coincided with rapid growth of small and medium-sized cities. The added level of detail in our study provides more nuanced entry points for national level vulnerability reduction.

We showed that key vulnerabilities, and their causes, were most severe for urban populations subject to the most rapid urbanization, or to the most rapid urban expansion. While the most rapid urbanization is overwhelmingly a phenomenon of LDCs, the most rapid urban expansion is overwhelmingly a phenomenon of LMICs. Looking forward, our results showed that both patterns of the most rapid coastal urbanization and the most rapid urban expansion were in direct conflict with current and future adaptation to climatic extremes in these urban areas. In socio-economic terms this conflict threatens to accentuate existing development gaps between LICs and HICs unless sweeping international efforts to scale up vulnerability reduction are successful.

A defining characteristic of the global picture of urban vulnerability profiles was asymmetry. The number and severity of typical socio-ecological problems among the profiles were distributed asymmetrically, and so were the positions to deal with these problems and reduce vulnerability. From a climate change mitigation perspective, rapid urbanization is desirable in high-income countries, and undesirable in developing countries without efficiency-increasing measures (Rybski et al. 2016). From a climate change adaptation perspective, we drew a sharper conclusion in view of future sea-level rise, and the potential increase of cyclone and flooding frequency and intensity: Rapid urbanization is undesirable in MICs without the presence of effective government, and *must* be accompanied by efficacy-increasing measures in LICs. Otherwise, rapid coastal urbanization increases the key vulnerabilities we identified.

Turning to vulnerability reduction, evident entry points for flood vulnerability reduction were to reduce the respective cause(s) of the profile-specific severe flood exposure. This, for example, means diverting rapid urban expansion from heavily populated and remaining unpopulated risk-prone low-lying areas, and from remaining wetlands. Entry points for flood vulnerability reduction in all profiles were to utilize and enhance

a) effective government-driven reduction of exposure and sensitivity, and
b) community-driven adaptive capacity of flood-sensitive slum populations.

However, it is clear that each of these measures requires efficient coordination of action from governmental and non-governmental actors on national to community levels. The Manila profile was a promising candidate (e.g. in the majority of The Philippines (Manila), Southern China (Guangzhou, Shanghai, Fuzhou), Vietnam (Da Nang), Bangladesh (Chittagong), and the Dominican Republic (Santo Domingo)). We explained the relative efficiency, or efficacy, in flood vulnerability reduction, despite low adaptive capacity and moderate government effectiveness with decades of accumulated experience in refining governmental *and* community-based responses to tropical cyclones and subsequent floods in highly exposed urban locations. On this basis we suggested two entry points for integrated national vulnerability reduction on community-based and governmental levels for urban areas belonging to this urban vulnerability profile:

1) scale up the impact of existing refined local community-based disaster responses - e.g. the successful community-based initiative of the Homeless People's Federation of the Philippines (Carcellar et al. 2011; Revi et al. 2014);
2) prioritize large-scale, government-led national projects, which require the efficacy inherent in this profile for the necessary leverage. These projects should focus on integrating „hard“ infrastructural adaptation, such as dike-building and land use planning, with "soft" measures such as wetland protection under sea-level rise and urban expansion.

Financial and human resources for vulnerability reduction are particularly limited for LMICs, making it particularly difficult to scale up successful reduction measures. Under these circumstances, we proposed to efficiently scale up successful reduction measures by transferring and tailoring them to cities with the same urban vulnerability profile, i.e. with a similar problem structure. Although this similar problem structure initially suggests a similar response to the same measure, the next step is to comprehensively test this, i.e. whether the typology of vulnerability is also a typology of adaptation measures. For drylands, evidence from over 20 case studies supported this hypothesis (Kok et al. 2015; Sietz et al. 2011). If proven correct in the RUCF, such "city matching" could support climate adaptation funds in spreading more targeted and effective reduction strategies under rapid coastal urbanization.

5.5 Typology Overlay

The global typologies of vulnerability for human populations in the rapidly urbanizing coastal fringe and in drylands are further steps towards a more complete causal and spatial understanding of socio-ecological vulnerability on a global scale. Coupling the different typologies makes sense, because they are not mutually exclusive, and because interactions between profiles of these typologies are evident. For example, in spatial and functional terms, the typologies are directly coupled in urbanizing and periurban areas in drylands, e.g. through adjacent drylands agriculture and unplanned urbanization (Portnov et al. 2004).

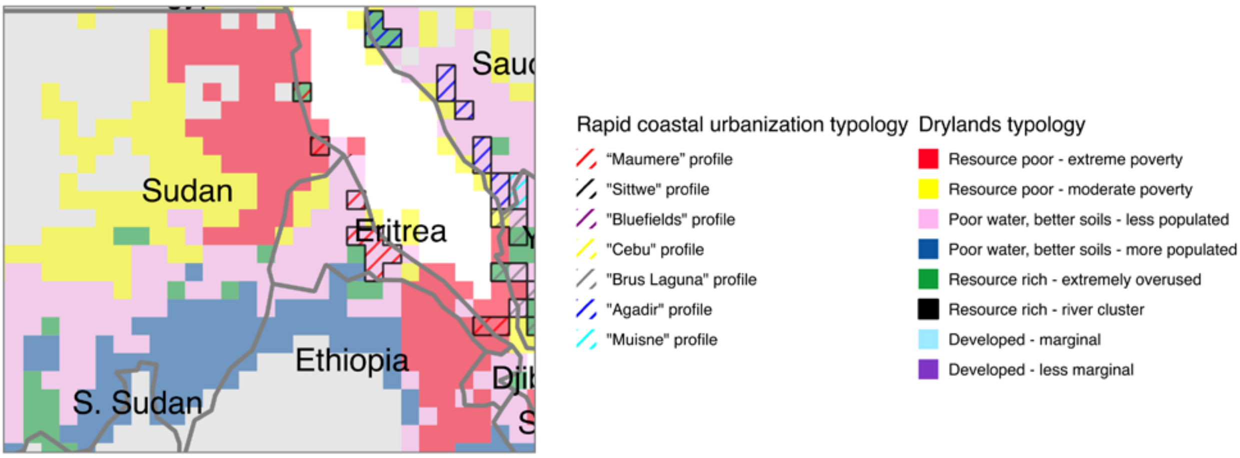

Figure 5.1: Spatial overlay of the drylands typology and the rapid coastal urbanization typology. Four profiles in the RUCF are particularly problematic: Both profiles with the fastest population increase and pronounced poverty under overstretched management (Group I, "Maumere" and "Sittwe" profiles), and two profiles with rapid population increase and the most rapid expansion, which intensify high flood damages under moderate adaptive capacity (Group II, "Bluefields" and "Cebu" profiles). Three profiles in drylands are particularly problematic: The resource poor profile under severe poverty (red), the water scarce profile with better soils under moderate poverty (grey), and the resource rich extremely overused profile (green).

We briefly investigated where the most problematic profiles from both typologies spatially coincide using a spatial overlay (Figure 5.1, example for Eritrea and Sudan). The overlay of the typologies shows that situations of vulnerability in drylands and vulnerability in the RCUF are particularly prolific in nine countries, of which seven are in Africa, one in The Caribbean, and one in Asia (Eritrea, Sudan, Mauritania, Cap Verde, Senegal, Angola, Madagaskar, as well as Haïti and Pakistan). In Eritrea, Sudan, and Haïti 100% of the rapidly growing urban areas are in the most vulnerable profiles of both typologies. Eritrea and Sudan are entirely classified as drylands, and the majority of these drylands are profiled as particularly vulnerable. In addition, all rapidly growing urban areas display extremely rapid urbanization and severe poverty under lowest adaptive capacities (red profile, RUCF). At the same time, the areas are generally resource scarce and severely impoverished (red profile, drylands), or water scarce with better soils under moderate poverty (grey profile, drylands). Therefore, the situation in these two countries can be considered the most problematic. In Mauritania and Cap Verde approx. half of the rapidly growing urban areas are in the most vulnerable profiles of both typologies. Both countries are entirely classified as drylands. In Senegal, Angola, Madagaskar, and Pakistan between approx. 10% and 50% of the rapidly growing urban areas are in the most vulnerable profiles of both typologies. Overall, this kind of overlay can serve as a basis for analyzing other related societal outcomes, e.g. migration, to identify policy-relevant circumstances that support or reduce the outcome in particularly affected countries. Section 0 is such an in-depth analysis for violent conflicts.

5.6 Lessons Learned

Like all scientific analyses, this dissertation comes with its shortcomings and limitations. I relate the most important ones to the research questions they pertain to in the following, starting with RQ2: With advances in its formalization and treatment of sensitivity, using the methodology used to address RQ 1, 2, and 4 produced meaningful results in different well-defined socio-ecological systems. The results were successfully plausibilized with a range of sources. However, implicit sensitivities and normative judgements remain in the clustering and interpretation steps, just like they are implicit in all indicator-based vulnerability analyses (Hinkel 2011). For example, there is no such thing as "the optimal" clustering method (Janssen et al. 2012). Results from clustering, and interpreting them, are sensitive to adding or removing indicators. In view of these sensitivities to choice, it was crucial to be as explicit as possible about the decision criteria used in each step of clustering, how these criteria were considered, and which decisions were made based on them. Finally, sensitivity analysis using other clustering methods, and comparing results between methods, could also be useful.

Turning to RQ 1, this dissertation identified general profile-based adaptation needs based on generalizing similar causes of vulnerability in different places. It did not identify profile-based adaptation options. Instead, it explored how adaptation measures in case studies (e.g. in community-based adaptation in slums in The Philippines) may be applicable to the entire vulnerability profile the study was located in. More systematic meta-analysis of adaptation case studies would be necessary to establish the link between an entire vulnerability profile and the portfolio of opportunities and policy response options. Therefore, more work is needed in field of plausibilizing profile-specific adaptation options, before establishing whether or not the profiles of vulnerability are also profiles of adaptation measures.

Turning to RQ 3, we learned that including political factors would likely further increase the understanding of what drives violent conflict in drylands. According to drylands vulnerability literature, political factors were not typically salient in shaping drylands vulnerability. Therefore, these factors were not included in the drylands analysis. However, from the conflict literature in drylands we learned that such factors can be important for driving violent conflict. Examples include political marginality (Adano et al. 2012; Buhaug 2010; Raleigh 2010) and political instability (Fearon et al. 2003). This warrants including such factors in future analysis. In spatially explicit analysis like ours this would be impeded by a lack of spatial and temporal datasets with subnational resolution (Blattman et al. 2010; Sietz et al.

2011). Once appropriate data does become available, including political factors would likely further reduce the unexplained variance in our statistical models for predicting violent conflict incidence.

5.7 Conclusions and Future Prospects

This dissertation increased the understanding of patterns of vulnerability for human populations in two socio-ecological systems with global distribution: the rapidly urbanizing coastal fringe, and drylands, including human security in drylands. We showed that the resulting causal and spatial patterns of vulnerability to multiple socio-economic and environmental stressors in these specific systems make sense. The resulting global overviews are further steps towards a more complete causal and spatial understanding of socio-ecological vulnerability of human populations on a global scale.

At first sight, the richness of knowledge from local and regional case studies of socio-ecological vulnerability in the systems of rapid coastal urbanization and drylands appear to be patchworks of distinct vulnerability analyses in unique places. This seems like an insuperable hurdle for finding more general characteristics and problem structures on a global level. By refining and using an indicator-based data-driven methodology, however, this dissertation confirmed that these patchworks are, in fact, systematically structurable and quantifiable into a limited number of global patterns of similar problem structures causing vulnerability. By providing step-by-step guidelines and comprehensively improving the sensitivity analysis we made an existing methodology readily applicable to any well-defined socio-ecological system. Testing the plausibility of the global patterns with an ample body of 34 studies and case studies substantiated the results (see list of case studies in Annex, Table 8).

This dissertation showed that causal patterns of vulnerability can not only be found in numerous places around the world in more rural socio-ecological systems (drylands), but also in urban socio-ecological systems. By doing so, this dissertation has provided useful new insights into underlying causes of socio-ecological vulnerability on the timely topic of rapid coastal urbanization. It is typical that global patterns of flood damage, cyclone damage, the most rapid population growth, the most rapid urban expansion, and mismanagement are stacked dramatically against the urban coasts which are most disadvantageously positioned to reduce these causes. We concluded that the resulting direct conflict between these patterns and efforts to reduce vulnerability to flooding and cyclones threatens to widen the development gap between LICs and HICs further, unless sweeping international efforts to scale up vulnerability reduction are successful. Our profiles provided entry points for structuring *where* to consider scaling up *which* measures between the local and the global level.

To address the crucial need to scale up successful measures under limited available resources in a more targeted manner, we suggested a comprehensive transfer of successful vulnerability reduction strategies between – and into - highly vulnerable areas in coastal cities and drylands, which share the same vulnerability profile. As a starting point, a common vulnerability profile membership is causal bedrock for showing between which areas “matching” and transfer make the most sense.

Socio-ecological vulnerability proved to be a useful concept for increasing the understanding of what drives the onset of violent conflict in drylands. The main reason is that our methodology accommodated for dependencies between factors (and variations in these dependencies), which were conceivably linked to violent conflict. This was more realistic than the static relationships in commonly used parametric approaches. Since our methodology outperformed a commonly used methodology in peace research for explaining conflict onset, further research applications of both a vulnerability framework and the methodology are warranted in human security studies in the future. Applications to other societal outcomes with conceivable links between socio-ecological vulnerability and GEC are warranted as well, such as the overexploitation of global commons, as suggested in GEO 4 (Jäger et al. 2007).

The profiles constituting the global overviews are useful complements to the fragmented mosaic of local and regional case studies. They allow for a more complete picture of adaptation needs. Importantly, they allow for statements about the myriad of locations or regions without case studies. Still, further research is required. Upcoming research needs to accommodate for the dynamic nature of vulnerability to GEC in socio-ecological systems. Therefore, follow-up studies need to determine to what extent the baseline typologies from this dissertation change over time by using modeled data for future time slices. This would require the analysis of scenario data projected by integrated assessment models. While we have done this for drylands (Lüdeke et al. 2014), the analogous analysis for the RUCF is still missing.

Causal patterns of socio-ecological vulnerability increased the understanding of what drives violent conflict in global drylands, so we suggest testing this in the global urban context in the next step. So far, regional to global data-driven research on the connection between rapid urbanization and violent conflict incidence is spurious (Buhaug et al. 2013). Yet whether violent conflict is "urbanizing" or not is a highly relevant question, now that humanity is increasingly becoming an urban species.

There is a chronic lack of financial and human resources for identifying adaptation needs under GEC. This makes finding general characteristics to draw conclusions for policy options all the more relevant. Overall, it can be concluded that generalizing similar causes of vulnerability in different places is a useful, sensible, and efficient supplement to local case studies for scaling up the identification of adaptation needs in any well-defined socio-ecological system. This applies to systems in largely rural and urban settings, which has not been established until now.

Annex

Supporting Material for Chapter 2

To discover how and where the patterns of vulnerability are manifest, we use cluster analysis (Everitt et al. 2001). This method classifies the gridded or local scale data into groups or clusters that share similar characteristics and that can be interpreted in terms of vulnerability characteristics (vulnerability profiles).

For our analysis we applied the well-established and computationally attractive K-means clustering algorithm that partitions the data-points into K groups (Mac Queen 1967). The results of using K-means will be sensitive to the starting point of the underlying search process for the optimal partitioning. Taking the results of hierarchical clustering using Ward's method (Ward 1963) for a random subset of the data as a starting point for the K-means clustering search was shown to have good performance (Milligan 1980). Since the clustering outcomes can also be sensitive to the scaling of the data we employed a min-max normalization that rescales the data to values between 0 and 1, before using K-means, as recommended by Milligan et al. (1988).

Central point in establishing the clustering is selecting the number K of clusters in which the dataset will be partitioned. We applied a procedure based on a notion of cluster-stability (Ben-Hur 2002) suggesting that the resulting clustering should ideally be stable/robust when repeating the clustering under different starting conditions and under perturbation or resampling of the data. By repeatedly comparing two cluster partitions performed with different random start-settings and counting the number of data points that were assigned to the same cluster in these two cluster partitions, we obtained an estimate of the fraction of data-points that were clustered similarly, that is the 'stable points'. By displaying the average fraction of data-points that are clustered similarly under resampling of the data, as a function of the number of clusters K (K=2, 3, … K_{max},), we obtained a so-called *consistency graph* (see figure A1a). This consistency graph can be used to find a suitable choice for the number of clusters, for example the K for which the consistency graph renders a (local) optimum.

In case that the consistency graph does not display only one local optimum, it is also possible to assess the 'optimal' clustering results for various K groups, by means of a branching diagram (see figure A1b). The branching diagram indicates which of the clusters will split when increasing the K groups and which one merge when decreasing K groups. Such a branching diagram gives useful information on the relatedness of the clusters for various numbers of K and can suggest which level of detail seems appropriate in striking a balance between spurious and accidental detail (large K) and obvious, low-informative groupings (small K).

Information on the importance of the various variables in the clustering process can be obtained by studying how sensitive the results are if we omit certain variables from the analysis, e.g. by fixing them at their mean-value (so-called 'blinding' of variables). A comparison of this 'blinded' clustering with the original partition with all variables fully included, by using a well-established measure for cluster-agreement (the adjusted Rand-index, introduced by Hubert and Arabie (1985)) leads to the so-called Fraiman index (Fraiman 2008) (see figure A1c). It provides values between 0 and 1 that express the importance of specific variables, with small values indicating the most important variables, since the clustering obtained when blinding these specific variables will not show much agreement with the original full variable clustering.

Having obtained a suitable number of groups, boxplots for the data-points in the specific clusters (see figure A1d), as well as profiles showing the average values of these data-points (see figure 1) can be used to examine characteristic features of the various clusters. This step in the analysis is the basis for a discussion of the important vulnerability dimensions for the identified clusters. A map showing the distribution of the clusters over the globe (see figure 2) renders additional information on the spatial structure/pattern of the clusters, which was not available from the boxplots and the profile.

In a box-plot the cluster centre (the average value which defines the profile) is indicated by a circle, and the spread around this centre is indicated by the box-boundaries that denote the lower and upper quartiles (the 25^{th} and 75^{th} percentiles) of the data; thus, the box-length indicates the interquartile distance (IQR). The band near the middle of the box denotes the median. The whiskers denote the minimum and maximum data values within 5^{th} and 95^{th} percentiles. So, 90 per cent of the objects within a cluster are located between these two points. Notice that the box-plots for the clusters only display one-dimensional information, as projected on the individual axes associated to the various variables. Information on the specific spatial structure of the cluster of points in the multidimensional data space, spanned by all variables considered, does not show up in the box-plot.

A comprehensive description of these clustering techniques can be found in Janssen et al. (2012).

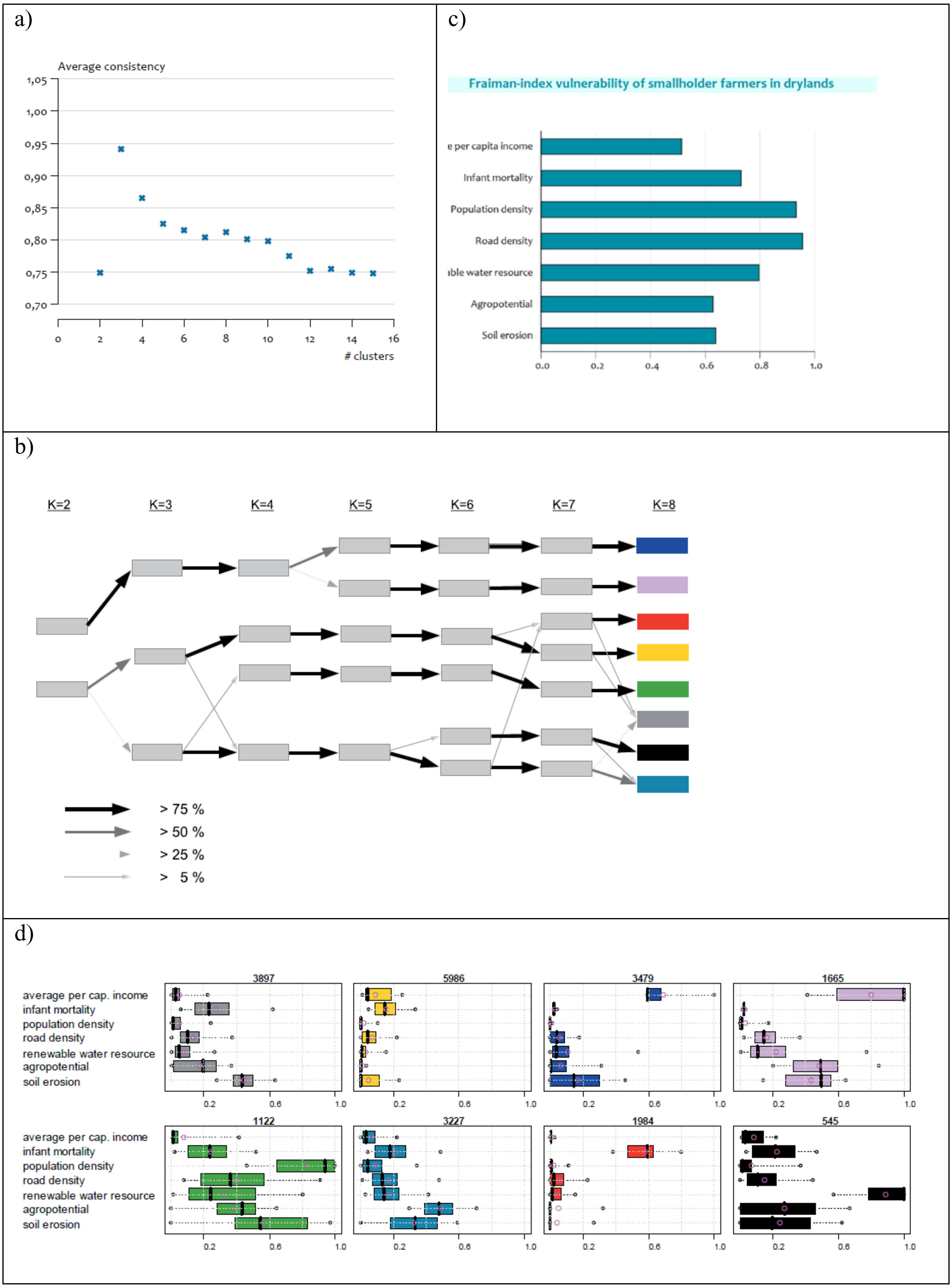

Figure A1: a) Consistency graph to determine the optimum number of clusters for the pattern of vulnerability of farmers in drylands; b) Branching diagram for the pattern of vulnerability of farmers in drylands; c) Fraiman measure for the pattern of vulnerability of farmers in drylands; d) Box plots for the pattern of vulnerability of farmers in drylands.

Supporting Material for Chapter 4

Indication

Some indicator datasets quantify changes over time (rather than a state) in order to accommodate for rapid coastal urbanization as a process. The selection of the temporal resolution to indicate change was guided by the most recent, globally complete time frame available for this ensemble of datasets. Data addressing a state is predominantly from 2000, and data addressing change is exclusively for the period from 1990 to 2000. A complete set of the georeferenced datasets for a more recent time frame was not available, partly because some datasets are not updated. The following paragraphs explain each indicator and reasons for its selection.

We differentiate urban population pressure in coastal urban areas into rapid urban population increase as the main driver, and urban expansion. The increase of urban dwellers over time relative to the existing urban population is the best indication of the scale of the unprecedented coastal urbanization (UNDESA 2006). We indicate this driver using relative urban population increase (Table 4.1) by calculating the urban population increase from 1990 to 2000, expressed in per cent, based on subnational urban population data on a 0.1° x 0.1° scale (Klein Goldewijk et al. 2010). Urban expansion, i.e. the rate at which urban areas are encroaching surrounding non-urban areas (including coastal ecosystems), is indicated using urbanized area change per grid cell from 1990 to 2000 with a spatial resolution of 0.1° x 0.1° (Klein Goldewijk et al. 2010). These two indicators are also employed in establishing the areas of interest for this study (see "spatial delineation" section).

A crucial factor for determining the differential vulnerability of the urban poor (as opposed to non-poor) is the slum population level (Mehrota et al. 2011). For an urban-specific quantification of marginalized populations we use the percentage of urban population living in poverty, proxied with a dataset of slum population in per cent of urban population in the year 2000 (UN-HABITAT 2008). The change of slum population from 1990 to 2000 was not used because of the high amount of country values missing for 1990. This would have excluded missing areas from the entire study, and compromised the goal of a global overview.

We use a measure of financial welfare to contextualize the urban population living in poverty through average national income. Average income is an important determinant of livelihoods and vulnerability. For this we apply a second indicator for poverty, i.e. average per capita income expressed by per capita GDP (The World Bank 2006; UNSTAT 2005). Combinations of indicator values of urban poverty and income provided interpretable insights into the prevalence of more vulnerable settlement types and livelihoods, and into distributions of income and inequality. Finally, average per capita income differentiated between coastal urban fringes in LICs, MICs, and HICs.

We assume that a measurement of how effectively governments handle managerial and planning challenges with its services and policies determines how urban governments are positioned to deal with novel and long-standing challenges. Therefore we quantify planning and management capacity with the government effectiveness dataset from the Worldwide Governance Indicators (WGI) dataset (Kaufmann et al. 2010). The government effectiveness indicator captures perceptions of the quality of public services, the quality of the civil service, and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. Interpreting values from this indicator with average per capita income also provides interpretable insights into the efficacy of planning and management to translate relative wealth into government effectiveness in the face of rapid global change.

We identified a lack of global datasets on ecosystems services for coastal urban areas. Therefore, we compiled a dataset on wetlands prevalence surrounding urban areas. We combined the prevalence of key wetlands per grid cell with the percentage to which wetlands immediately surround urban areas using wetlands distribution and urban-rural population distribution datasets (CIESIN 2005a; Lehner et al. 2004). While changes in prevalence are not accounted for due to a lack of further time slices for the input data, combinations of this indicator with the urban area change rate indicator help understand the distribution of the pressure of urban expansion on ecosystem functions and services of wetlands.

Quantifying climate-related floods and cyclones is key, because lives and livelihoods are particularly exposed and sensitive to them in coastal cities (Handmer et al. 2012). We use the high-resolution database of natural hazard frequency and mortality distributions from Dilley et al. 2005. Scrutiny of the definitions for the database's frequency and mortality distributions for these two extreme events concluded that they respectively denote occurrence and damage. This allows for quantifying these components of extreme event vulnerability on a comparable basis. Cyclone and flood occurrence are indicated by using the respective frequency datasets (Dilley et al. 2005). Cyclone frequency is based on storm tracks, and flood frequency is based on ocean-based and river-based flood events. The cyclones and flood damages are indicated by using the respective datasets of annual relative cyclone and flood hazard mortality rates (Dilley et al. 2005). These datasets are based on local and regional hazard specific mortality records from 1981-2000. The data was aggregated and averaged from the original spatial resolution of 2.5' x 2.5' to 0.5° x 0.5° grid cells.

Finally, we take into account that population growth in low-lying areas is increasing exposure by putting an increasing number of settlements at risk to sea level rise and sea level extremes. Factors generating vulnerability to inundation include long-term climate change-related sea level rise, but also the related increase of base heights of climatic extreme event-related coastal floods (Seneviratne et al. 2012). Other further influences on relative sea level rise in coastal urban areas exist, e.g. ground-related processes such as subsidence and salt water intrusion. We acknowledge this and broadly indicate overall population exposure to sea level rise beyond climate change-related factors alone. For this we calculated the urban population percentage per grid cell living in areas up to 2m above sea level, using urban population data (Klein Goldewijk et al. 2010), urban land cover data from MODIS, and the digital elevation model STRM90 v4.1 (Jarvis et al. 2008). While sea level rise is projected to rise by 0.52 to 0.98m by 2100 compared to 1985-2005 for RCP8.5 (Church et al. 2013), an additional increased incidence and/or magnitude of extreme high sea level is considered likely in the early 21st century, and very likely by the late 21st century (IPCC 2013). There is a high confidence that extremes will increase with mean sea level (Seneviratne et al. 2012). Regional differences in the aforementioned forces determining sea level rise were not considered because of limitations of datasets with global coverage.

Data Resolution and Preparation

In this paper we understand urbanization as an increase in urban population. This population-driven definition allows for the use of high resolution urban population and area change data that applies consistent definitions over time (UNDESA 2012; Grubler et al. 2012). In principle, our approach to constitute a global overview takes cities and urban areas of all population sizes into account. Motivated by the availability of global subnational raster data for the selected indicators, we specify urban areas using established high-resolution rasterized urban population data as opposed to using administrative boundaries. Furthermore, there is a lack of city-specific datasets with global coverage for the majority of socio-economic and biophysical indicators used. This applies for small- and medium-sized cities in particular.

We delineate the area of interest – i.e. the rapidly urbanizing coastal fringe - using data for 0.5°lon x 0.5°lat grid cells with a) above-average urban population growth; b) coastal proximity; and c) and minimum urban population (see “spatial delineation” section). This reduces 66,663 land grids cells to a mask of 2036 cells (2.7 % of total land area, see the next section for details on the criteria applied for this reduction).

A high subnational spatial resolution of the datasets is desirable. This allows for sufficient differentiation within heterogeneous coastal zones, and for resolving distinctive properties that set these zones apart from the hinterland and non-urbanized coastal zones. The criterion of high subnational resolution is met for all biophysical datasets and - crucially - for datasets indicating urban population and area increase. As a result subnational datasets were used for 8 out of 11 indicators (Table 1).

All datasets for the cluster analysis with a different initial resolution than 0.5°lon x 0.5°lat were aggregated or disaggregated to this resolution. For the proxy datasets with higher spatial resolution this meant averaging or summing up values within each 0.5° grid cell. For the three datasets with national values, this meant assigning country values to each grid cell centroid within a country.

Only grids cells with a complete set of 11 indicators are admitted to the cluster analysis. The 11 datasets were checked for correlation. Two out of 55 pairs revealed a correlation coefficient above 0.6, which is significant at the .05 level: Flood exposure and flood sensitivity (0.62), and cyclone exposure and cyclone sensitivity (0.73). This can be explained by the multitude of cyclones-sensitive LICs with limited means for adaptation exposed to tropical cyclones and flooding. However, the correlation does not outweigh including both in the clustering: Including both components of vulnerability for floods and cyclones was crucial in this vulnerability analysis, and the vulnerability profiles reveal distinct differences between exposures and sensitivities. Per capita GDP and government effectiveness have a correlation of 0.54 at the .05 level, showing that higher income countries tend to have more effective governments. Both signify important aspects of adaptive capacity in view of urbanization. They show different degrees of importance for shaping the typology. The correlation does not outweigh including both in the cluster analysis in this case either. Income is not used to construct the government effectiveness indicator.

Socio-economic data with subnational resolution and global coverage is not always readily available. For this reason national datasets were used for average per capita income, urban population in poverty, and government effectiveness.

Spatial Delineation of the Rapidly Urbanizing Coastal Fringe

In the first step, all grid cells intersecting a buffer reaching 50 kilometers inland from the world’s coastlines were selected using the IMAGE land-ocean coastline (Stehfest et al. 2014). From these coastal grid cells we selected cells with a total urban population exceeding 1000. This ruled out purely rural coastal populations, It also ruled out grid cells with markedly low country thresholds for defining what an “urban” settlement is (e.g. 250 inhabitants for Norway) from unbalancing more commonly applied higher thresholds (Svirejeva-Hopkins 2008). Finally, only coastal urban grid cells with an annual urban population change of at least 2.25% from 1990 to 2000 were selected. This change rate denotes above average, or rapid, urban population increase - of at least 25% from 1990 to 2000 - according to the UN World Urbanization Prospects (UNDESA 2008). The resulting mask overwhelmingly comprises areas in LICs and MICs. This is in line with these countries being the locus of rapid urbanization (UNDESA 2012, 2008).

Cluster Analysis

Before the cluster analysis is applied all the indicators are normalized to a 0-1-range using their minimum and maximum values. Each indicator is fed in to the cluster analysis with the same weight. We applied the widely known partitioning K-means method (Macqueen 1967). The initial partition for the algorithm was delivered by a hierarchical clustering, using the Ward-method on a subset of the data (Ward 1963).

The data points, i.e. the grid cell within the rapidly urbanizing coastal mask, are assigned to the k given initial clusters. Then the centers of the clusters are calculated and subsequently the objects are assigned to the nearest cluster centers. This procedure minimizes the total within-cluster sum-of-squares (TSS) criterion until a breakup criterion is reached.

The optimal number of clusters is determined by analyzing the stability of the different partitions for various numbers of clusters. Thereby the algorithm is repeated 400 times with changing initial conditions. We compare the resulting cluster partitions pairwise. For each pair we calculate a consistency measure showing how much the two partitions vary, and then average the results over the 200 pairs. A lower variety and a higher consistency measure for a pre-given number of clusters imply a higher similarity between the clusters and the underlying structure in the data. The method belongs to the stability based methods (Ben-Hur et al. 2002; Roth et al. 2002).

Studies Used for Plausibilizing Profiles in Chapter 4

Table 3: Studies and case studies used.

No.	Study	Profile(s)	Information which plausibilizes the profile(s)	Country or region
1	Garschagen, M. & Romero-Lankao, P. 2013. Exploring the relationships between urbanization trends and climate change vulnerability.	"Maumere" profile (red) – Most rapid urbanization and most severe poverty under lowest adaptive capacity	Combination of high slum population levels, the most rapid urbanization and overstretched urban management	LDCs, national level
2	Cohen, B. 2006. Urbanization in developing countries: Current trends, future projections, and key challenges for sustainability.	"Maumere" profile (red) – Most rapid urbanization and most severe poverty under lowest adaptive capacity	Combination of high slum population levels, the most rapid urbanization and overstretched urban management	LDCs, national level
3	Hanson, S. et al. 2011. A global ranking of port cities with high exposure to climate extremes.	"Maumere" profile (red) – Most rapid urbanization and most severe poverty under lowest adaptive capacity	Cities belonging to this profile, such as Qingdao, Xiamen, Lomé, and Rangoon, are expected to have high increase rates of population exposed to flooding in the upcoming decades due to projected sea level rise, greater storm surges, and subsidence.	Large port cities
4	Brecht, H., Deichmann, U. & Wang, H.G. 2013. A Global Urban Risk Index.	"Sittwe" profile (black) – Multiple severe biophysical and socio-economic problems under widespread poverty	Higher flood and cyclone damages, exacerbating the group I specific severe socio-economic problems of urban poverty, high slum levels, and overstretched management: The African cities in this profile are considered the most at risk to cyclones in all of Africa.	Selected African cities in this profile
5	Button, C. et al. 2013. Vulnerability and resilience to climate change in Sorsogon City, the Philippines: learning from an ordinary city?	"Sittwe" profile (black) – Multiple severe biophysical and socio-economic problems under widespread poverty	Combination of higher flood and cyclone damages, severe socio-economic problems of urban poverty, high slum levels, and overstretched management. High risk to cyclones.	Sorsogon City, The Philippines
6	McCarney, P. et al. 2011. Cities and Climate Change - The challenges for governance.	"Sittwe" profile (black) – Multiple severe biophysical and socio-economic problems under widespread poverty	Absorption of burgeoning population increase through marginalization of the poor in dense informal settlements. This worsens existing risks for poor households.	Developing countries
7	Tanner, T. et al. 2009. Urban Governance for Adaptation: Assessing Climate Change	"Sittwe" profile (black) – Multiple severe biophysical and socio-economic problems	Absorption of burgeoning population increase through marginalization of the poor in dense informal settlements.	Ten Asian cities

	Resilience in Ten Asian Cities.	under widespread poverty	This worsens existing risks for poor households.	
8	De Sherbinin, A., Schiller, A. & Pulsipher, A. 2007. The vulnerability of global cities to climate hazards.	"Brus Laguna" profile (grey) - High flood damages from rapid urban expansion and reduced natural protection	Vulnerability to current climate hazards; high flood occurrence, fast-paced urban expansion, reduced natural flood protection, and relatively high totals of low-lying settlement translating into high flood damages.	Rio de Janeiro, Brazil
9	De Sherbinin, A., Schiller, A. & Pulsipher, A. 2007. The vulnerability of global cities to climate hazards.	"Cebu" profile (yellow) – Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement	Moderate slum population levels and very low income indicate low adaptive capacity to reduce the very high flooding and cyclone damages. The relatively high marginalization of the poor, low income, and rapid growth suggest that the low-lying settlement areas are also inhabited by marginalized informal settlements.	Shanghai, China
10	UN-HABITAT 2007. Global Report on Human Settlements - Enhancing Urban Safety and Security.	"Cebu" profile (yellow) – Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement	High percentage of informal settlements at risk to coastal flooding make up 35% of the population	Manila, The Philippines
11	Hanson, S. et al. 2011. A global ranking of port cities with high exposure to climate extremes. Nicholls, R.J. et al. 2007. Ranking Port Cities with High Exposure and Vulnerability to Climate Extremes.	"Cebu" profile (yellow) – Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement	Global ranking of population numbers in large port cities which are exposed to current coastal flooding shows that three of the four highest ranked cities are located in this profile (Shanghai, Guangzhou, and Kolkata).	Large port cities most exposed to current coastal flooding
12	Hanson, S. et al. 2011. A global ranking of port cities with high exposure to climate extremes. Nicholls, R.J. et al. 2007. Ranking Port Cities with High Exposure and Vulnerability to Climate Extremes.	"Cebu" profile (yellow) – Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement	Present flood damages shows a high vulnerability to sea level rise due to its superimposition on coastal floods and storm surge levels. Other cities in this profile, i.e. Shanghai, Guangzhou, Kolkata, Chittagong, and Ningbo, will be among the cities most exposed to coastal flooding in the 2070s due to sea level rise and storm surge.	Large port most cities exposed to future coastal flooding
13	Gupta, A.K. & Nair, S.S. 2010. Flood risk and context of land-uses: Chennai city case.	"Bluefields" profile (purple) – High damages and moderate occurrence of climate extremes: most severe climate change vulnerability	Overstretched management - Uncontrolled urban expansion, inter alia, has increased coastal and riverine flooding. The flooding overwhelms a lacking flood control response and drainage systems. Under these circumstances, relatively high wetlands prevalence alone does not significantly reduce high flood and cyclone-related sensitivity.	Chennai, India

14	UN-HABITAT 2011. Cities and Climate Change - Global Report on Human Settlements.	"Bluefields" profile (purple) – High damages and moderate occurrence of climate extremes: most severe climate change vulnerability	Extreme sensitivity to floods and storm surges - even moderate flooding events have largely affected the urban poor.	Dhaka, Bangladesh
15	Douglas, I. et al. 2008. Unjust waters: climate change, flooding and the urban poor in Africa.	"Bluefields" profile (purple) – High damages and moderate occurrence of climate extremes: most severe climate change vulnerability	Extreme sensitivity to floods and storm surges - even moderate flooding events have largely affected the urban poor.	Maputo, Mozambique
16	El-Raey, M. 2009. Coastal Areas - Impact of Climate Change: Vulnerability and Adaptation.	"Agadir" profile (dark blue) – No severe problems under less rapid population increase and highest adaptive capacity	Flood occurrence can increase in the future through a combination of continued rapid urban expansion into wetlands (and other low-lying areas), and sea level rise. This has been suggested as a threat to unplanned rapid urbanization in coastal cities on the Arabian Peninsula	Coastal cities, Arabian Peninsula
17	Tolba, M.K. & Saab, N.W. 2009. Arab Environment: Climate Change Impact of Climate Change on Arab Countries.	"Agadir" profile (dark blue) – No severe problems under less rapid population increase and highest adaptive capacity	Lack of precaution: The advantageous conditions to adapt to increasing flood exposure may lead to ignoring climate change adaptation requirements.	Urban planning regulations in the Arab region
18	Luque, A., Edwards, G. & Lalande, C. 2013. The local governance of climate change: new tools to respond to old limitations in Esmeraldas, Ecuador.	"Muisne" profile (light blue) - Extreme flood sensitivity damage under relative wealth and least rapid population increase	Explanation for such flood sensitivity: Marginalization of the poor in flood-prone areas under conditions of great socio-economic disparities, and a high differential impact of floods.	Esmeraldas, Ecuador
19	De Sherbinin, A., Schiller, A. & Pulsipher, A. 2007. The vulnerability of global cities to climate hazards.	"Muisne" profile (light blue) - Extreme flood sensitivity damage under relative wealth and least rapid population increase	Explanation for such flood sensitivity: Marginalization of the poor in flood-prone areas under conditions of great socio-economic disparities, and a high differential impact of floods.	Mumbia, India
20	Mukheibir, P. & Ziervogel, G. 2007. Developing a Municipal Adaptation Plan (MAP) for climate change: the city of Cape Town.	"Muisne" profile (light blue) - Extreme flood sensitivity damage under relative wealth and least rapid population increase	In addition to the above, informal low-lying settlements are lacking drainage infrastructure. Under these circumstances the high wetlands prevalence alone is insufficient to reduce major flood sensitivity.	City with pronounced social disparities: Cape Town, South Africa

21	Revi, A., Satterthwaite, D.E., Aragón-Durand, F., et al. 2014. Urban Areas. In Climate Change 2014: Impacts, Adaptation, and Vulnerability.	"Muisne" profile (light blue) - Extreme flood sensitivity damage under relative wealth and least rapid population increase	In addition to the above, informal low-lying settlements are lacking drainage infrastructure. Under these circumstances the high wetlands prevalence alone is insufficient for reducing major flood sensitivity.	City with pronounced social disparities: Mumbai, India

Studies Used for Plausibilizing Results in all Publications

Table 4: Studies and case studies used for plausibilizing the results of each publication.

No.	Study	Publication (Chapter)	Profile(s)	Information which plausibilizes the profile(s)	Country or region
1	Siebert, S., Feick, S., Hoogeveen, J. 2005. A digital global map of irrigated areas – An update for Asia.	Drylands (2), Conflict (3)	Both high income country profiles (pink, lilac)	Distribution and classification of irrigated cropland	Global
2	FAO 2006. Livestock's long shadow: environmental issues and options.	Drylands (2), Conflict (3)	Both high income country profiles (pink, lilac)	Distribution of livestock production systems	Global
3	Geist, Helmut J, Lambin, E.F. 2004. Dynamic Causal Patterns of Desertification.	Drylands (2), Conflict (3)	Both high income country profiles (pink, lilac), resource poor, severe poverty profile (red)	Less fertile and overused rangelands; desertification through exacerbation of natural resource situation by extensive or nomadic grazing	Europe, Australia, global drylands
4	Le Sage, A. & Majid, N. 2002. The Livelihoods Gap: Responding to the Economic Dynamics of Vulnerability in Somalia.	Drylands (2), Conflict (3)	Resource-poor, sever poverty profile (red)	Pastoral land-use	Somalia
5	Kassahun, A., Snyman, H.A. & Smit, G.N. 2008. Impact of rangeland degradation on the pastoral production systems, livelihoods and perceptions of the Somali pastoralists in Eastern Ethiopia.	Drylands (2), Conflict (3)	Poor water, better soils vulnerability profiles (blue)	Rangeland degradation, overuse of agro-potential by an increasing population resulting in poor human well-being	Rural areas of Eastern Ethiopia
6	Ifejika Speranza, C., Kiteme, K., Wiesmann, U. 2008. Droughts and famines: The underlying factors and the causal links among agro-pastoral	Drylands (2), Conflict (3)	Poor water, better soils vulnerability profiles (blue)	Combination of low human well-being and high soil degradation under population pressures	Rural areas of Southern Kenia

	households in semi-arid Makueni district, Kenya.				
7	Ram, K. A., Tsunekawa, A., Sahad, D. K., Miyazaki, T., 1999. Subdivision and fragmentation of land holdings and their implication in desertification in the Thar Desert, India.	Drylands (2), Conflict (3)	Resource rich profile (green)	Causes of deteriorating land productivity	Khabra Kalan, Rajastan, India
8	Mustafa and Qazi 2007. Mustafa, D. & Qazi, M.U. 2007. Transition from Karez to Tubewell Irrigation: Development, Modernization, and Social Capital in Balochistan, Pakistan.	Drylands (2), Conflict (3)	Rivers profile (black)	Causes of increasing social disparities and degradation of environmental resources	Balochistan, Indus basin, Pakistan
9	Markakis, J., 1995. Environmental Degradation and Social Conflict in the Horn Of Africa. The Debate: Context and Perspective.	Conflict (3)	Resource-poor, severe poverty profile (red); poor water, better soils profile, more populated (blue); poor water, better soils profile, les populated (pink)	Classic example of environmental degradation	Horn of Africa (Ethiopia, Eritrea, Somalia, and Djibouti)
10	Raleigh, C. et al. 2006. Conflict Sites 1946–2005. UCDP/PRIO Armed Conflicts Dataset Codebook.	Conflict (3)	Resource-poor, severe poverty profile (red); poor water, better soils profile, more populated (blue); poor water, better soils profile, les populated (pink)	Conflicts involving the Afar people and the states of Ethiopia, Djibouti, and Eritrea	Horn of Africa (Ethiopia, Eritrea, Somalia, and Djibouti)
11	Berhe, T. & Adaye, Y. 2007. The impact of local conflict on regional stability.	Conflict (3)	Resource-poor, severe poverty profile (red); poor water, better soils profile, les populated (pink)	Inter-clan conflict over scarce resources as a major conflict cause	Afar and Issa tribes, Horn of Africa
12	Rettberg, S. 2010. Contested narratives of pastoral vulnerability and risk in Ethiopia's Afar region.	Conflict (3)	Resource-poor, severe poverty profile (red); poor water, better soils profile, les populated (pink)	Cut-off of Afar's resource base from important land and water resources; conflict over grazing lands the Afar were forced off of	Afar tribe, Horn of Africa
13	Getachew, K.N. 2001. Among the Pastoral Afar in Ethiopia: Tradition, Continuity and Socio-Economic Change.	Conflict (3)	Resource-poor, severe poverty profile (red); poor water, better soils profile, les populated (pink)	Cut-off of Afar's resource base from important land and water resources	Afar tribe, Horn of Africa
14	Garschagen, M. & Romero-Lankao, P. 2013. Exploring the relationships between urbanization trends and climate change vulnerability.	Urban (4)	"Maumere" profile (red) – Most rapid urbanization and most severe poverty under lowest adaptive capacity	Combination of high slum population levels, the most rapid urbanization and overstretched urban management	LDCs, national level

15	Cohen, B. 2006. Urbanization in developing countries: Current trends, future projections, and key challenges for sustainability.	Urban (4)	“Maumere” profile (red) – Most rapid urbanization and most severe poverty under lowest adaptive capacity	Combination of high slum population levels, the most rapid urbanization and overstretched urban management	LDCs, national level
16	Hanson, S. et al. 2011. A global ranking of port cities with high exposure to climate extremes.	Urban (4)	“Maumere” profile (red) – Most rapid urbanization and most severe poverty under lowest adaptive capacity	Cities belonging to this profile, such as Qingdao, Xiamen, Lomé, and Rangoon, are expected to have high increase rates of population exposed to flooding in the upcoming decades due to projected sea level rise, greater storm surges, and subsidence.	Large port cities
17	Brecht, H., Deichmann, U. & Wang, H.G. 2013. A Global Urban Risk Index.	Urban (4)	“Sittwe” profile (black) – Multiple severe biophysical and socio-economic problems under widespread poverty	Higher flood and cyclone damages, exacerbating the group I specific severe socio-economic problems of urban poverty, high slum levels, and overstretched management: The African cities in this profile are considered the most at risk to cyclones in all of Africa.	Selected African cities in this profile
18	Button, C. et al. 2013. Vulnerability and resilience to climate change in Sorsogon City, the Philippines: learning from an ordinary city?	Urban (4)	“Sittwe” profile (black) – Multiple severe biophysical and socio-economic problems under widespread poverty	Combination of higher flood and cyclone damages, severe socio-economic problems of urban poverty, high slum levels, and overstretched management. High risk to cyclones	Sorsogon City, The Philippines
19	McCarney, P. et al. 2011. Cities and Climate Change - The challenges for governance.	Urban (4)	“Sittwe” profile (black) – Multiple severe biophysical and socio-economic problems under widespread poverty	Absorption of burgeoning population increase through marginalization of the poor in dense informal settlements. This worsens existing risks for poor households.	Developing countries
20	Tanner, T. et al. 2009. Urban Governance for Adaptation: Assessing Climate Change Resilience in Ten Asian Cities.	Urban (4)	“Sittwe” profile (black) – Multiple severe biophysical and socio-economic problems under widespread poverty	Absorption of burgeoning population increase through marginalization of the poor in dense informal settlements. This worsens existing risks for poor households.	Ten Asian cities
21	De Sherbinin, A., Schiller, A. & Pulsipher, A. 2007. The vulnerability of global cities to climate hazards.	Urban (4)	“Brus Laguna” profile (grey) - High flood damages from rapid urban expansion and reduced natural protection	Vulnerability to current climate hazards; high flood occurrence, fast-paced urban expansion, reduced natural flood protection, and relatively high totals of low-lying settlement translating into high flood damages.	Rio de Janeiro, Brazil
22	De Sherbinin, A., Schiller, A. & Pulsipher, A. 2007. The vulnerability of global cities to climate hazards.	Urban (4)	“Cebu” profile (yellow) – Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement	Moderate slum population levels and very low income indicate low adaptive capacity to reduce the very high flooding and cyclone damages. The relatively high marginalization of the poor, low income, and rapid growth suggest that the low-lying settlement areas are also inhabited	Shanghai, China

				by marginalized informal settlements.	
23	UN-HABITAT 2007. Global Report on Human Settlements - Enhancing Urban Safety and Security.	Urban (4)	"Cebu" profile (yellow) – Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement	High percentage of informal settlements at risk to coastal flooding make up 35% of the population	Manila, The Philippines
24	Hanson, S. et al. 2011. A global ranking of port cities with high exposure to climate extremes. Nicholls, R.J. et al. 2007. Ranking Port Cities with High Exposure and Vulnerability to Climate Extremes.	Urban (4)	"Cebu" profile (yellow) – Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement	Global ranking of population numbers in large port cities which are exposed to current coastal flooding shows that three of the four highest ranked cities are located in this profile (Shanghai, Guangzhou, and Kolkata).	Large port cities most exposed to current coastal flooding, global selection
25	Hanson, S. et al. 2011. A global ranking of port cities with high exposure to climate extremes. Nicholls, R.J. et al. 2007. Ranking Port Cities with High Exposure and Vulnerability to Climate Extremes.	Urban (4)	"Cebu" profile (yellow) – Extreme flood and cyclone damages are hitting fastest expansion and highest totals of low-lying settlement	Present flood damages shows a high vulnerability to sea level rise due to its superimposition on coastal floods and storm surge levels. Other cities in this profile, i.e. Shanghai, Guangzhou, Kolkata, Chittagong, and Ningbo, will be among the cities most exposed to coastal flooding in the 2070s due to sea level rise and storm surge.	Large port most cities exposed to future coastal flooding, , global selection
26	Gupta, A.K. & Nair, S.S. 2010. Flood risk and context of land-uses: Chennai city case.	Urban (4)	"Bluefields" profile (purple) – High damages and moderate occurrence of climate extremes: most severe climate change vulnerability	Overstretched management - Uncontrolled urban expansion, inter alia, has increased coastal and riverine flooding. The flooding overwhelms a lacking flood control response and drainage systems. Under these circumstances, relatively high wetlands prevalence alone does not significantly reduce high flood and cyclone-related sensitivity.	Chennai, India
27	UN-HABITAT 2011. Cities and Climate Change - Global Report on Human Settlements.	Urban (4)	"Bluefields" profile (purple) – High damages and moderate occurrence of climate extremes: most severe climate change vulnerability	Extreme sensitivity to floods and storm surges - even moderate flooding events have largely affected the urban poor.	Dhaka, Bangladesh
28	Douglas, I. et al. 2008. Unjust waters: climate change, flooding and the urban poor in Africa.	Urban (4)	"Bluefields" profile (purple) – High damages and moderate occurrence of climate extremes: most severe climate change vulnerability	Extreme sensitivity to floods and storm surges - even moderate flooding events have largely affected the urban poor.	Maputo, Mozambique
29	El-Raey, M. 2009. Coastal Areas - Impact of Climate Change: Vulnerability and Adaptation.	Urban (4)	"Agadir" profile (dark blue) – No severe problems under less rapid population increase and highest adaptive capacity	Flood occurrence can increase in the future through a combination of continued rapid urban expansion into wetlands (and other low-lying areas), and sea level rise. This has been suggested as a threat to unplanned rapid	Coastal cities, Arabian Peninsula

				urbanization in coastal cities on the Arabian Peninsula.	
30	Tolba, M.K. & Saab, N.W. 2009. Arab Environment: Climate Change Impact of Climate Change on Arab Countries.	Urban (4)	"Agadir" profile (dark blue) – No severe problems under less rapid population increase and highest adaptive capacity	Lack of precaution: The advantageous conditions to adapt to increasing flood exposure may lead to ignoring climate change adaptation requirements.	Urban planning regulations in the Arab region
31	Luque, A., Edwards, G. & Lalande, C. 2013. The local governance of climate change: new tools to respond to old limitations in Esmeraldas, Ecuador.	Urban (4)	"Muisne" profile (light blue) - Extreme flood sensitivity damage under relative wealth and least rapid population increase	Explanation for such flood sensitivity: Marginalization of the poor in flood-prone areas under conditions of great socio-economic disparities, and a high differential impact of floods.	Esmeraldas, Ecuador
32	De Sherbinin, A., Schiller, A. & Pulsipher, A. 2007. The vulnerability of global cities to climate hazards.	Urban (4)	"Muisne" profile (light blue) - Extreme flood sensitivity damage under relative wealth and least rapid population increase	Explanation for such flood sensitivity: Marginalization of the poor in flood-prone areas under conditions of great socio-economic disparities, and a high differential impact of floods.	Mumbia, India
33	Mukheibir, P. & Ziervogel, G. 2007. Developing a Municipal Adaptation Plan (MAP) for climate change: the city of Cape Town.	Urban (4)	"Muisne" profile (light blue) - Extreme flood sensitivity damage under relative wealth and least rapid population increase	In addition to the above, informal low-lying settlements are lacking drainage infrastructure. Under these circumstances the high wetlands prevalence alone is insufficient to reduce major flood sensitivity.	City with pronounced social disparities: Cape Town, South Africa
34	Revi, A., Satterthwaite, D.E., Aragón-Durand, F., et al. 2014. Urban Areas. "Urban Areas." In Climate Change 2014: Impacts, Adaptation, and Vulnerability.	Urban (4)	"Muisne" profile (light blue) - Extreme flood sensitivity damage under relative wealth and least rapid population increase	In addition to the above, informal low-lying settlements are lacking drainage infrastructure. Under these circumstances the high wetlands prevalence alone is insufficient to reduce major flood sensitivity.	City with pronounced social disparities: Mumbai, India

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Declaration of Authorship

I, Till Sterzel, declare that this dissertation titled “Analyzing global typologies of socio-ecological vulnerability – The cases of human security in drylands, and rapid coastal urbanization” and the work presented in it are my own. I prepared this dissertation without illegal assistance. I confirm that the work is original except where indicated by special reference in the text and no part of the dissertation has been submitted for any other degree. This dissertation has not been presented to any other University for examination, neither in Germany nor in another country.

Till Sterzel

Potsdam, February 2018